DEFECT DETECTION USING AN OPTIMIZED AND INNOVATIVE PROCESSING TECHNIQUE OF THERMOGRAPHY IMAGES

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Abstract

The vision technology and in particular the thermography testing (TT) is a rapid developing NDE method within the nuclear industry. This paper proposes a new approach based on TT and anomaly detection algorithms for the detection of defects in nuclear components. The novelty of the approach consists of using a processing method, originally developed for multi- and hyperspectral imagery, for the automatic and unsupervised processing of thermography images. Practicability of the lock-in and pulsed thermography (LT and PT, respectively) are experimentally investigated by using reference samples containing different surface and sub-surface anomalies such as open cracks, and closed notches with different sizes and depths. The heating is carried out with Eddy current approach. The generated Eddy-current is launched on the specimen for different time periods and frequencies. Both, heating and cooling parts of the temporal signals are used. Principal component thermography is used to reduce the data space dimension of the acquired thermal sequences, and thus permits the decrease of the processing time. After the reduction of the data space dimension, anomaly detection algorithms are applied on the reduced data cubes. The influence of the size of the reduced data spaces on the anomalies detection is studied using the false alarm rate as evaluation criterion of the detection results obtained from two anomaly detection algorithms: the well-known Reed and Xiaoli Yu detector (RX) and a spatially adaptive version, the regularized adaptive RX (RARX).

The investigations show that; in the case where the targets are small and have significant temperature values, their signal spaces are kept after the reduction of the data cube dimensionality; the optimal false alarm rates are obtained when 80 – 86 % of the variance proportion of the projected data is considered. Indeed, with a detection of 80 – 90 % of the anomalies, we obtain optimal false alarm rates with a dimensionality which does not exceed 10 components, for both surface and subsurface defects.

Keywords: Anomaly detection, Surface inspection, NDT, Infrared thermography

1. INTRODUCTION

Different kinds and shapes of metallic parts (steel, stainless steel, aluminium, etc.) are used in several industrial areas such as the automotive, aviation, and nuclear domains. These components are very often inspected during the production or maintenances steps for quality control purposes. Inspection, which is a quality control task, is defined by Newman and Jain [1] as a process of determining if a product deviates from a given set of specifications. The inspectors are provided with lists and descriptions of unacceptable product defects such as cracks or surface blemishes for example.

Depending on the quality control requirements (number of parts to be examined, size of defects to be detected, etc.), the products are examined manually or automatically during the production or the manufacturing processes. Various non-destructive testing (NDT) techniques exist in the literature [2]. The choice of the appropriate technique primary depends on the type of anomalies to be detected (for metal parts, e.g., anomalies are often either surface defects (scratches, dents, etc.) or subsurface defects (certain types of cracks or porosities, etc.) which are internal discontinuities and cannot be seen visually).

Automated visual testing (AVT) concerns surfaces and also the subsurfaces parts of components. As an example, the examination weld structures of nuclear components encompasses the early detection of inter-dentritic propagating cracks.
Inspection of surface and sub-surface defects has become a critical task for manufacturers who strive to improve product quality and production efficiency.

Such kind of defects can affect the functionality, stability, safety of the components and therefore of complete installations. Large and obvious surface defects such as cracks, indents, scraps and scratches are usually inspected by AVT systems, where image processing techniques play a crucial role.

The detection of surface and sub-surface defects has been the subject of several researches for the inspection of metallic industrial components by means of NDT techniques. NDT is an examination, test, or evaluation performed on an object of any type, size, shape or material without changing or altering that object in any way, in order to determine the absence or presence of discontinuities that may have an effect on the usefulness or serviceability of that object. NDT may also be conducted to measure other test object characteristics, such as size; dimension; configuration; or structure, including alloy content, hardness, and grain size [2]. Nondestructive Evaluation (NDE) is a term that is often used interchangeably with NDT. NDE may be used to determine material properties such as fracture toughness, formability, and other physical characteristics [3]. Nondestructive testing and evaluation NDT&E methods are required to be reliable, economical, sensitive, user friendly and fast [4]. Although, NDT cannot guarantee that failures will not occur, it plays a significant role in minimizing the possibilities of failure. Several NDT techniques such as liquid penetrant testing, magnetic particle testing (MT), radiographic testing (RT), ultrasonic testing (UT), and thermography testing (TT) have been used for material inspection. Each of these NDT techniques has appropriate and adequate treatments to inspect the objects. In liquid penetrant testing, only surface breaking defects can be detected; surface preparation is critical as contaminants can mask defects; relatively smooth and nonporous surface are required; and chemical handling precautions are necessary (toxicity, fire, waste). In MT, only ferromagnetic materials can be inspected; smooth surfaces are relatively required; paint or other nonmagnetic coverings adversely affect sensitivity; and demagnetization and post cleaning is usually necessary. In RT, access to both sides of the structure is usually required; relatively expensive equipment investment is required; and possible radiation hazard for personnel. In UT, skill and training required is more extensive than other technique; surface finish and roughness can interfere with inspection; thin parts may be difficult to inspect; and linear defects oriented parallel to the sound beam can go undetected. TT is an imaging technology, which is contactless and completely non-destructive and secure. Since the temperature is one of the most useful parameter that indicates the structural health of an object, TT is used to detect surface and sub-surface defects by determining the surface temperature of the object using an IR camera.

We focus in this paper on infrared thermography (IRT) techniques. IRT is a non-intrusive temperature measuring technique for producing an image of the infrared light – invisible to our eyes – emitted by objects due to their thermal condition. IRT is a NDT method, with the advantages of being fast; easy to apply; applicable to all situations as long as there is a temperature difference on the surface of the inspected object; and providing non-contact, non-interaction, real-time measurements over a large detection area – instead of point or line – with a long range. IRT can only detect defects which cause a change in heat flow or the surface temperature of the item.

Defects detection and material inspection methods in IRT have gone through several progressive steps. Classical thermography is based on the visual interpretation of the thermographic images. The heating or the cooling anomalies are observed after the application of the heat. Defects that produce subtle temperature differences in the thermal images are generally not detected. Furthermore, this technique is based on temperature information only and can be susceptible to emissivity or uneven heating variations. Detection of subsurface defects can be greatly enhanced by the real time capture of a series of thermal images and the subsequent analysis of these images using various image processing algorithms, where defects not readily observable can be detected and quantitatively characterized [5]. Various techniques including: image normalization [6], thermal contrast calculations [7], pulsed phase thermography (PPT) [8] and principal component thermography (PCT) [9, 10] have been developed to remove emissivity or uneven heating variations so as to increase defect contrast and inspection depths.

We propose in this paper a new approach for the inspection of surface and sub-surface metallic parts. The proposed approach is based on the use of IRT techniques, PCT and hyperspectral imagery (HSI) algorithms. Lock-in and pulsed thermography (LT and PT, respectively) techniques are used to heat the inspected specimen and its thermal behaviour recorded during the heating and the cooling periods.
PCT is then used to reduce the data space of the acquired data cubes, where a subspace signal is estimated in order to work on space of smaller dimension than the original space of the data. After the dimensionality reduction of the data cube, HSI algorithms – dedicated to remote sensing applications – are applied on the reduced dataset images, where the anomalies are detected in an unsupervised way.

The novelty of this paper consists of the combination of these two techniques, TT and HSI detection algorithms. It is shown that this approach leads to a new unsupervised and generic examination procedure, as different defect types can be revealed with one processing method. We illustrate our purpose with experiences on two metallic parts containing respectively open notches with different sizes, and open cracks. Two thermography techniques, LT and PT, were applied to the samples and dataset of thermal images were created. The goal of this paper is to apply anomaly detection algorithms on the elaborated dataset images in order to detect surface and subsurface existing anomalies within the inspected samples. Only unsupervised algorithms are investigated, where no prior knowledge about the defects is known.

The remainder of this paper is organized as follows. Section 2 recalls the main thermography techniques dedicated to faults detection in IRT images. The proposed approach is described in Section 3. Section 4 reviews some existing algorithms from HSI literature dedicated to anomaly detection. Section 5 shows the experimental procedure and the used setup. The results are discussed there and Section 6 concludes this work.

2. INFRARED THERMOGRAPHY

Since the early 1960s, thermal testing has been successfully used, in many applications as a NDT&E technique to measure the surface temperature variations in response to induced energy. The energy creates a temperature contrast at material discontinuities that can be detected by an infrared (IR) camera [6]. The IR cameras detect radiation in the IR range of the electromagnetic spectrum (roughly $3 \text{–} 5 \mu m$ and $8 \text{–} 14 \mu m$) and generate false color images of IR or thermal emission called thermograms, allowing very sensitive non-contact temperature measurement [11]. IRT is also used for defect characterization and material property evaluation and inspection since it is completely noncontact and may be faster than many other techniques that are being used. Due to its noncontact character that allows for quick 2D surface mapping, it represents a powerful tool for NDE of materials and structures.

IRT is being used in a wide range of areas, such as in agriculture, civil engineering and architecture, diagnosing electrical and mechanical equipment, automotive industry, medicine and biology, manufacturing industry, food quality control and protection of historic heritage.

IRT can be divided into two approaches usually indicated as passive and active thermography. The passive approach tests materials and structures, which are naturally at different (often higher) temperature than ambient. The temperature is monitored without employing any heating of the sample induced by the measurement procedure. Features of the temperature distribution, like differences with respect to a reference level, allow to obtain qualitative information about the specimen under examination. Important applications of the passive approach are in production, predictive maintenance, medicine, fire forest detection, building thermal efficiency survey programs, road traffic monitoring, agriculture and biology. Contrary to the passive approach, in the active approach, an external stimulus is necessary to induce relevant temperature differences not present otherwise. Knowing the characteristics of this external stimulus (example: time $t_0$ when it is applied), active thermography allows to obtain both qualitative and quantitative evaluations by monitoring the transient of the temperature change induced in the anomalies by means of adequate artificial light emitting heating techniques, such as e.g. flashes or direct current (DC) lamps, lasers or other light sources [12].

Currently commonly used infrared thermography methods are active methods. Depending on the way of thermal excitation, different approaches of active thermography have been developed, such as step heating, PT and LT [13]. In step heating, the temperature rise is monitored in the transient domain, where a long heating pulse is applied. In PT, a short heating pulse is applied to the specimen and the cooling data is monitored in the transient domain. LT is carried out in stationary domain, where a modulated heat wave is launched on the sample, travels through the bulk by diffusion and reflects back from the defect sites. PT is being routinely used for quantitative evaluation of defect in both metallic and composite specimens.
LT has been extensively used to find quantitative information of subsurface defects, corrosion protective paints, morphologies of defects (like circular, square-like, etc.).

3. PROPOSED METHOD

The acquired thermal images are grouped in a sequence of thermograms, (Fig. 1a), where the first two dimensions represent the spatial information (pixel positions) and the third dimension represents the variation of the temperature for each pixel over the time, and gives the temperature profile (Fig. 1b). This data structure is remindful of the hyperspectral cubes which have the same data structure except that the third dimension represents the spectral response of each pixel with respect to the wavelength position. Fig. 1 shows a thermogram sequence with respect to the acquisition time and the temperature profile for the pixel \(p\) on coordinates \((i,j)\). \(\Delta t\) is the sampling time. Hence, the use of multi- and hyperspectral imaging algorithms on thermographic data for defect detection is possible. Actually, the thermal response of a material can be considered as representative of this material. It has been already shown in [14] that is possible to apply HSI algorithms, such as target and anomaly detection algorithms and spectral distance measures, for surface defect detection of metal parts on such pseudo-spectral-cubes corresponding to the different lighting modalities: white light and monochromatic lights in combination with polarization.

![Fig. 1: (a) thermograms sequence and (b) temperature profile for the pixel \(p\) on coordinates \((i,j)\).](image)

We propose in this paper a new defect detection approach based on anomaly detection algorithms for thermography images. The acquired thermal images are arranged in a 3D matrix, called cube or data cube, in ascending order of acquisition time (Fig. 2a). The defect detection is based on the time behaviour of each pixel, where the anomalies are defined as observations that deviate in some way from the background from a statistical point of view.

![Fig. 2: (a) data cube dimensions, (b) thermogram at \(t_{500}\) and (c) temperature rise and decay curves for three different objects.](image)

The observed temporal responses are composed of two main successive components corresponding, respectively, to the heating (temperature rise) and the cooling (temperature decay) processes of the specimen (Fig. 2c). Usually, the behaviour of the specimen is analyzed only either during the rising surface temperature or during the decay [8]. Most often, in PT the temperature decay part is used to analyze the inspected parts [12]. Basically, the specimen is briefly heated for a certain period of time and then it is allowed to cool. In parallel, its temperature profile is recorded. At time \(t_1\), before heat reaches the specimen’s surface, a cold image is captured. The temperature of the material rises during the pulse. After the pulse, it decays because the thermal energy propagates by diffusion under the surface.
Later, the presence of a subsurface defect reduces the diffusion rate so that when observing the surface temperature, such a subsurface defect appears as an area of higher temperature with respect to the surrounding sound area. Fig. 2 shows the data cube construction from the thermograms sequence. It also shows a thermogram example at $t_{500}$ and plots the temperature rise and decay curves for three pixels of different parts: the heating tool, background and defect. The limit between the heating and cooling parts (HP and CP, respectively) is plotted with respect to the heating tool (black curve). The limits of the background and defect pixels, red and blue curves respectively, are slightly shifted with respect to the heating tool pixel, due to the thermal front propagations and to the distance separating them from the heating tool.

![Fig. 2](image)

Fig. 2: shows the data cube construction from the thermograms sequence.

It also shows a thermogram example at $t_{500}$ and plots the temperature rise and decay curves for three pixels of different parts: the heating tool, background and defect. The limit between the heating and cooling parts (HP and CP, respectively) is plotted with respect to the heating tool (black curve). The limits of the background and defect pixels, red and blue curves respectively, are slightly shifted with respect to the heating tool pixel, due to the thermal front propagations and to the distance separating them from the heating tool.

![Fig. 3](image)

Fig. 3: proposed scheme of the presented approach based on SVD and HSI algorithms.

The proposed approach can now be schematized. Fig. 3 illustrates the main steps involved in this approach. As a first step, either the entire datacube, recorded by the IR thermal camera, is treated or spatial and temporal regions of interest (ROIs) can be selected. The spatial ROI corresponds to the desired area to be inspected, while the temporal ROI corresponds to HP and/or CP (Fig. 2c), or to any part of the temporal profile want to be considered. Once the desired ROIs are chosen, the datacube is unfolded into a matrix and singular value decomposition (SVD) is applied, allowing to decompose it into N components, arranged in a descending order of the corresponding singular values (SVs), where the first components contain the maximum variance.

In PCT, the thermographic data is projected from its original space to its eigenspace to increase its variance and reduce its covariance [9, 10, 13]. SVD extracts the spatial and temporal information from the thermographic matrix in a compact manner. SVD is close to principal component analysis (PCA) with the difference that SVD simultaneously provides the PCAs in both row and column spaces. The 3D thermogram cube representing time and spatial variations is reorganised as a 2D $M \times N$ matrix $A$, where $M$ is the total number of pixels and $N$ is the total number of images. Under this configuration, the matrix $A$ can be decomposed into three matrices $U$, $S$ and $V$ as follows [9, 10]:

$$A = \sum_{i=1}^{N} U_i S_i V_i^T$$  \hspace{1cm} (1)

The columns of matrix $U$ consists of singular vectors that represent the spatial variation of the data set. The matrix $S$ is a diagonal matrix with the singular values on its diagonal, which are reordered in descending order based on their values. The columns of matrix $V$ are the right singular vectors that represent the temporal variation of the data set. Usually, original data can be adequately represented with only a few components. Typically, a 1000 thermograms sequence can be replaced by 10 or less components [13].

A reduction of the data space is often used, where a subspace signal is estimated in order to work on smaller dimension than the original space of the data. In general, the space reduction leads to a loss of information, especially for targets that have low spatial dimensions (represented by only a few pixels). In our case, the targets are small, but due to the fact that they have significant temperature values, their respective signal spaces are preserved after the reduction of the data cube dimensionality.

Anomaly detectors are then applied on the reduced datacube in order to detect the defects with a non-supervised approach. This means that no prior knowledge about the defects is used. The detection results are given as 2D maps which will be used next to evaluate and compare the detection algorithms by means of the receiver operating characteristic (ROC) curves.
4. ANOMALY DETECTION ALGORITHMS

The observed data cube is considered as a set of $M = M_x \times M_y$ vectors in the full multidimensional space (Fig. 2a). More often, the task of a detection algorithm is to decide, by means of a statistical hypothesis test, whether a target of interest is present or not in a pixel-under-test with observed pixel vector $x$ [15]. To take a decision, we calculate a test value $y = D(x)$, and compare it to a threshold $\eta$. A practical question of paramount importance for a detection algorithm user is how to set the threshold to keep the total number of detection errors (target misses and false alarms) small. Indeed, there is always a compromise between choosing a low threshold to increase the probability of (target) detection (PD) and a high threshold to keep the probability of false alarm (PFA) low. For any given detector, the trade-off between PD and PFA is described by the ROC curve, which plots PD ($\eta$) versus PFA ($\eta$), as a function of threshold.

In the literature, many algorithms for detection and classification are proposed, applied in multi- and hyperspectral imagery. The most popular unsupervised detectors are the anomaly detection algorithms, which do not require any knowledge of the spectral signatures of the target of interest (defect). Anomalies are defined with reference to a model of the background. Background models are developed adaptively using reference data from either a local neighbourhood of the test pixel or a large section of the image. Anomalies are defined as observations that deviate in some way from the neighbouring clutter background or the image-wide clutter background, respectively [16].

The problem of anomaly detection is typically formulated as a binary test between two hypotheses: background only ($H_0$) or target and background ($H_1$):

$$ y = D(x) \begin{cases} \overset{H_1}{\gtrsim} \eta \\ \overset{H_0}{<} \eta \end{cases} \tag{2} $$

The most common used anomaly detector is the Reed and Xiaoli Yu detector (RX) given by [16, 17]:

$$ D_{RX}(x) = (x - \mu)^T \hat{\Sigma}^{-1}(x - \mu) \begin{cases} \overset{H_1}{\gtrsim} \eta \\ \overset{H_0}{<} \eta \end{cases} $$

where $\hat{\Sigma}$ and $\mu$ are respectively the estimated covariance matrix and mean vector of the reference background data. In order to obtain good estimations of the mean and the covariance matrix, using the whole data, the background must be homogeneous and the target must be small. Basically, $D_{RX}(x)$ estimates the Mahalanobis distance between the pixel vector $x$ and the mean background, which is zero for centred data [15]. This algorithm has the constant false alarm rate (CFAR) property, it assumes that the background follows a local Gaussian multivariate distribution, that the spatial signature of the target is known, and that the covariance matrix is unknown [18].

Recently, a new approach of RX, A regularized adaptive RX (RARX), was proposed in [18] to estimate the spatial distribution conjointly with the detection algorithm. Its expression is given by:

$$ D_{RARX}(x_i) = \frac{1}{\hat{\Sigma}_{xy}} \left[ \frac{||\hat{x}_i||^2}{2} + 2 \sum_{l \in V(i)} \hat{s}_l \hat{x}_l^T \hat{x}_i \right] \tag{4} $$

where $\hat{s}_l$ is an estimation of the abundance of the tested pixel $x_i$ in its neighbour $x_l$, which can be calculated by the following expression:

$$ \hat{s}_l = \frac{\hat{x}_l^T \hat{x}_i}{||\hat{x}_i|| \||\hat{x}_l||}^2 $$

$k = 1..V$

$\hat{x}$ is the whitened vector, and $s = [s_1, s_2, ..., s_V]^T$, where $V$ is the number of neighbour pixels.

The first term in Eq. (4) is similar to Eq. (3), and the second one is a linear correlation between $x_i$ and its neighbours, weighted by the estimated spatial distribution of the target in the neighbourhood. This term linearly depends on $\hat{s}_l$.

5. APPLICATION

Two samples, containing different anomalies, were used in order to validate our proposed approach. The considered samples are listed in Table 1. A dataset of thermography images was elaborated with different anomalies, where two recording processes, PT and LT, were considered.
The recording setup is made of an IR-camera, an inductor (for eddy-current excitation) and a sample. The camera is placed at a certain distance and angle to the surface in order to have constant lateral resolution and avoiding disturbing reflections (in case of high emissive surfaces, e.g.). Fig. 4 depicts the recording setup.

<table>
<thead>
<tr>
<th>Sample name</th>
<th>S1</th>
<th>S2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample photo</td>
<td><img src="image1" alt="Image" /></td>
<td><img src="image2" alt="Image" /></td>
</tr>
<tr>
<td>Anomaly type</td>
<td>Open notches with different sizes</td>
<td>Open cracks</td>
</tr>
<tr>
<td>Material</td>
<td>Inconel 600</td>
<td>Inconel 600</td>
</tr>
<tr>
<td>Defect size</td>
<td>Length: 5 mm, Depth: 2 mm</td>
<td>Length: 8 mm, Width: 20 µm (approximately)</td>
</tr>
</tbody>
</table>

Table 1: considered samples for the thermography reference dataset.

The current generator is used to generate eddy currents (also called Foucault currents), which are electric currents induced within conductors by a changing magnetic field induced by the conductor. The heating effect is caused by the effective resistance of the conductor through which the eddy current is flowing. During the heating process, the currents propagate in the vicinity of the inductor. They are propagating in the upper part of the sample, and they also are disturbed by the presence of the defects.

In PT, a short heating pulse is generated and launched for a few seconds (from 1 to 10 s) on the specimen through the inductor and in LT, a sinusoidal wave of low frequency (form 1 to 5 Hz) is generated and applied for 5 to 10 s. In both processes, LT and PT, the specimen is left to cool for 5 to 10 s. The IR camera images the temperature variations as thermograms during the heating and cooling phases with a frequency of acquisition of 62 fps and sends the acquired images to the computer, where the output data of each sequence is stored as a cube of size $[M \times N]$, i.e. $(M \times N \times N)$ signal vectors of length $N$.

Usually, the behaviour of the inspected object is analyzed only either during the surface temperature rise or during its decay [8]. As the anomaly detection is based on the temporal behaviour of the pixels, it is very important to choose the relevant part (heating and/or cooling parts), where the anomaly pixels are well separated from the other pixels. A comparative study was done in [19] based on the criterion of false alarm rate (FAR). For automated inspections, it has been suggested to keep the whole provided information about each pixel and to choose both regions: heating and cooling parts, of the temperature profile. This will avoid the problems of how to choose the temporal ROI and how to find the limits between the heating and cooling parts. In addition, dimensionality reduction methods will be applied on the data cubes in order to work with cubes in reduced data spaces, where only relevant components will be kept and the anomalies can be easily detected, for sufficient temperatures. We have kept the totality of the cube in order to have the best estimation of the data subspace.
We have chosen for this study two cubes, corresponding to LT and PT, for each sample. For the two used samples, S1 and S2, (Lock-in 4 Hz and Pulsed 4s) and (Lock-in 1 Hz and Pulsed 5s) cubes were selected, respectively.

SVD is then applied on the selected data cubes, where the original data are projected in subspaces of dimension $K$. The images in the resulting cubes are arranged in descending order of the variance $r. r = \frac{\sum e_i^2}{\sum e_i^T e_i}$, where $e_i$ is the $i^{th}$ eigenvalue on the diagonal matrix $S$ described in Eq. (1). In this experiment, we varied the values of $K$ from 2 to 15. This corresponds to a variance $r$ of 80 – 86%.

The described algorithms in Eqs. (4) and (5) are then applied on the reduced data cubes with different values of $K$, where the detection results are given as 2D masks after thresholding the detection maps. We varied the probabilities of detection from 40% to 90% and we calculated the corresponding false alarm rates. The results are shown in Fig. 5. Since both algorithms RX and RARX have given similar results, we show only the results of RARX.

The false alarm rates vary from 0% to 0.66% for S1-Lock-in and from 0% to 0.03% for S1-Pulse. The anomalies present in S1 are mostly detected with very low false alarm rates in both lock-in and pulse cubes only with a detection of 40% of the pixels of the defect. These anomalies are easily detected with low false alarm rates because the defects are located on the surface of the sample and are visible in all the acquired thermograms, which means that after data space reduction step, they are present and with high energy. Also, their thermal profiles are different from those of the pixels of the background and the heating tool, which make easy to detect them with the used anomaly detection algorithms.

Concerning S2, the false alarm rates vary a lot from each detection rate. But, the optimal rates are obtained with a detection of 40% of the pixels of the defect. The false alarm rates vary from 0.06% to 1.68% and from 0.19% to 3.84% for S2-Lock-in and S2-Pulse respectively. These rates can reach, respectively, 26.74% and 15.32% for S2-Lock-in and S2-Pulse when high detection rates (80 – 90%) are fixed. The main reason of these high false alarm rates is that, there is an additional, compared to S1, class of pixels (the pixels where the heating tool is reflected on the surface); in addition to the other classes (background, defect and heating tool); which have also significant temperature values.

Fig. 5: probabilities of false alarm for $K = 2: 15$ and detection rates for two specimens acquired with LT and PT.
In fact, the signal spaces of both classes defect and reflexion are kept after the reduction of the data cube dimensionality. This is the reason why the pixels of these 2 classes appear in the detection masks, as shown in Table 2.

Table 2 shows the detection masks (binary cards) for different detection rates (30 – 90 %) with the optimal value of $K$.

<table>
<thead>
<tr>
<th>Probability of detection</th>
<th>30 %</th>
<th>40 %</th>
<th>60 %</th>
<th>80 %</th>
<th>90 %</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1 Lock-in</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S1 Pulse</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S2 Lock-in</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S2 Pulse</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

Table 2: detection masks for different probabilities of detection.

Knowing that we are looking for linear anomalies corresponding to linear defects and in order to detect only the pixels corresponding to the anomaly, the probability to detect all the pixels of the anomaly should be kept low (30 – 40 %). In such cases, the pixels of the defect can be easily detected with very low false alarm rates.

A comparison study has been done between the use of the original and reduced data cubes. The results in Table 3 show that the detection times are approximately 10 times greater when reduced data cubes are used compared to when original data cubes are used, however the false alarm rates are greatly reduced. The computational burden of the used anomaly detection algorithms depends directly on the size $(Mx \times My \times N)$ of the input data cube, which is expressed in terms of big O notation for both algorithms, RX and RARX, as $O(Mx My N)$ after calculation of the covariance matrix. This means that these algorithms scale to increasing amounts of data. For a data cube of size $120 \times 160 \times 900$; the detection time is about 9 s, the dimension reduction time is about 90 s and the detection after reduction with $K = 2$ is about 2 s. However, the SVD calculation time could be reduced by using a reduced version of SVD, such as truncated SVD to determine only the first components.

<table>
<thead>
<tr>
<th>Original data cube</th>
<th>Reduced data cube</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (pixels)</td>
<td>Detection time (s)</td>
</tr>
<tr>
<td>S1-LT 88x163x927 7.84 19.69</td>
<td>88x163x3 56.06 2.06 0</td>
</tr>
<tr>
<td>S1-PT 128x163x959 10.96 24.94</td>
<td>128x163x2 114.62 2.95 0</td>
</tr>
<tr>
<td>S2-LT 124x163x824 9.45 48.56</td>
<td>124x163x2 94.31 2.87 0.56</td>
</tr>
<tr>
<td>S2-PT 124x163x952 10.94 98.17</td>
<td>124x163x2 101.87 2.84 3.58</td>
</tr>
</tbody>
</table>

Table 3: Comparison between original and reduced data cubes.
6. CONCLUSION

In this paper, an unsupervised approach of surface and sub-surface defects detection for the inspection of nuclear metallic components has been proposed. It is based on the use of thermography images and anomaly detection algorithms, basically dedicated to remote sensing applications. A dataset of thermal cubes, where the thermal profile of the inspected surface is recorded, has been established for two metallic parts containing different types of anomalies by means of LT and PT techniques. Both rising and decay parts of the temperature profile have been considered, which means that the whole information about the temporal behaviour of each pixel have been used. The space dimensions of the data cubes were then reduced by means of SVD in order to work with smaller data spaces than the original ones. The reduced data cubes have been analyzed by means of anomaly detection algorithms to obtain the existing anomalies within the inspected parts with no prior knowledge about the defects. The detection maps, resulting from the used algorithms RX and RARX, have been compared for different dimensions of the reduced dataspaces and different detection rates of the anomaly pixels. The results show that the detection strategy allows to detect compact anomalies with very low false alarm rates when low detection rates are fixed. The results are better when there is only three main classes: background, heating tool and defect pixels and no additive perturbation pixels are present on the scene corresponding the reflexion of the heating tool on the surface. Compared to detection on original data cubes, the inspection time in the proposed approach is significantly increased, but the detection performances are substantially improved with the use of dimension reduction. Moreover, the use of the reduced version of SVD, such as truncated SVD to determine only the first components, should be much quicker and more economical than the full SVD.

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