

Infrared thermography- a study into its current capabilities and future prospects

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Abstract

The fourth industrial revolution has brought forward a paradigm shift in the analyses and interpretation of data. Emerging technologies such as artificial intelligence, Internet of Things (IoT), and cyber physical systems have accelerated the process of concepts such as decentralised decision making, automation, and digitalisation. In the context of Non-destructive Evaluation (NDE), adopting these technologies has substantially improved the efficiency of existing techniques. Currently, Ultrasound Testing (UT) has been dubbed as the “gold standard” for Non-destructive Testing (NDT). However, a major drawback to this technique is its contact-based inspection. Infrared Thermography (IRT) on the other hand offers a non-contact non-intrusive inspection and is a growing area of interest to researchers. This paper explores the impact of infrared thermography within the maintenance industry. Firstly, the current state-of-the-art in IRT is presented followed by the limitations of the technique, the current research and knowledge gap that exists in thermographic testing. Potential solutions that can overcome the limitations are proposed. These cover specific aspects of the technique such as the working principle, mathematical modelling, data interpretation and processing, automation, and digitalisation. Finally, future prospects of the technique are briefly presented.

Keywords: infrared thermography; nondestructive testing; automation; defect detection; condition monitoring; digitalisation; artificial intelligence.

1. Introduction

Data interpretation can be defined as the process where one reviews existing data to draw relevant conclusions with the help of various analytical methods and tools. Data analysis comprises of categorising, manipulating, and summarising relevant data to answer critical research questions [1]. The advent of industry 4.0 has revolutionised the way in which these two processes are carried out. While there are instances where knowledge extraction from apparent data is a straightforward task, this is not the case most of the time. This is where technologies and concepts such as decentralised decision making, automation, artificial intelligence, and digitalisation can really push the boundaries of gaining new and valuable insights from available data. It also allows for handling much larger volumes of data (Big Data) than previously possible. The shift to “smart” enterprises has impacted a variety of industries, driving changes on a fundamental level such as healthcare, transport, utilities, and the energy sector [2].

Digital transformation has left very little room for analogue modes of data transmission. It has also led to a vast amount of man-made information being created solely in the digital form. In the context of Non-destructive Testing (NDT), adopting new emerging technologies and practices has allowed for

more accurate and reliable measurements as well as incorporating hybrid inspection, leveraging more than just one NDT technique. Current trends are focused on Additive Manufacturing (AM) [2], [3] which offers new possibilities towards the design and manufacturing of products. The technique can create lighter structures which offer a range of advantages where weight is a critical factor without compromising its structural integrity (e.g., aerospace components). It allows for more complex geometries to be manufactured that are either not possible or are more expensive to manufacture using traditional means. Applications of AM parts span over several industries such as the biomedical, aerospace and automotive industries [4], [5], [6]. The rising interest in AM has also driven researchers to evaluate various NDT techniques that can effectively evaluate the structural integrity of these components. Currently, there are several techniques that have shown their feasibility in evaluating AM parts such as Acoustic Emission (AE), X-ray Computed Tomography (CT), thermography, Ultrasound Testing (UT), laser line scanning, computer vision, and structured light testing [7]. At present it has been shown that CT leads as the NDT technique that can sufficiently inspect AM parts

with complex geometries to qualify their usage in safety critical environments [8].

The title of the most extensively used NDT technique goes to Ultrasound Testing (UT) [9]. This is due to its numerous advantages that include fast, safe, and economically beneficial inspections. It makes use of sound waves of frequencies higher than 20kHz that are not in the range of human hearing. Its applications extend to a vast number of industries. Recent studies have also focused on machine learning combined with UT [10]. With increasing computational power, numerically computing more realistic UT cases has become possible. However, there are several drawbacks to this technique. The biggest setback in UT inspection is that it is a contact-based measurement technique. It requires a coupling medium such as a water-based gel between the testing probe and the object under inspection. Moreover, the surface finishing of the component being tested must be smooth to get a good signal-to-noise ratio. Furthermore, it requires the wave propagation speed to be known a priori since the velocity of sound waves is affected by the density and the elasticity of the medium it is travelling through [11]. Lastly, the training required to carry out UT is more extensive and expensive than other NDT techniques such as Infrared Thermography (IRT).

IRT on the other hand offers a fast, non-contact, and non-intrusive inspection. It makes use of the electromagnetic radiation, that is emitted by any object whose temperature is above 0K. Like the previously mentioned NDT techniques, its applications span over a range of industries. It has the capability to detect both surface and sub-surface damage. Pulsed thermography which is a subset of IRT has seen significant development in recent years to establish itself as a robust NDT technique to detect near and sub-surface damage, especially in composite materials [12]. It offers several advantages over traditional NDT techniques such as dye penetrant, magnetic particle, and visual inspection as these techniques struggle to determine the structure health of the component due to their heterogeneity and layer-based build. Other techniques such as UT and radiography struggle to fully characterise damage due to localised density differences and sound attenuations. Furthermore, it is a visual based technique which gives it a competitive edge over other techniques such as Magnetic Flux Leakage (MFL) and Phased Array Ultrasound testing (PAUT).

This paper seeks to explore the current impact of IRT in the NDT industry. Furthermore, it outlines the areas of research that need to be explored to overcome the current limitations of thermography. A brief theoretical background to the technique is presented including some of its applications. This is followed by an overview of the current state-of-the-art, along with emerging trends, highlighting the

direction in which the research is heading. This will lead to the current knowledge gap that is hindering the path of further development in infrared technology. Lastly, potential solutions to address the current knowledge gap are theorised. These solutions are envisioned from a wholistic perspective on IRT rather than focusing on specific aspects of the inspection process which includes decision making based on the data obtained from the inspections.

2. Theory and Applications of IR thermography

Infrared thermography fundamentally relies on the electromagnetic emission of an object.. According to Planck's law, assuming that there is no net flow of energy between a body and its environment the total radiated energy by a body increases with temperature and the peak emission shifts towards shorter wavelengths [13]. This phenomenon is illustrated in Figure 1. The term blackbody refers to any object that absorbs and emits all incident electromagnetic radiation that falls on it regardless of the angle or frequency.

The vertical red dashed lines indicate the part of the electromagnetic spectrum in the visible range. The figure below shows that for a blackbody to emit electromagnetic radiation in the visible range, the temperature of that object will have to be between 4000 to 8000K. For objects that are in a standard room temperature ($\approx 24^\circ\text{C}$), their peak emission would be in the infrared range of 700nm to 1mm.

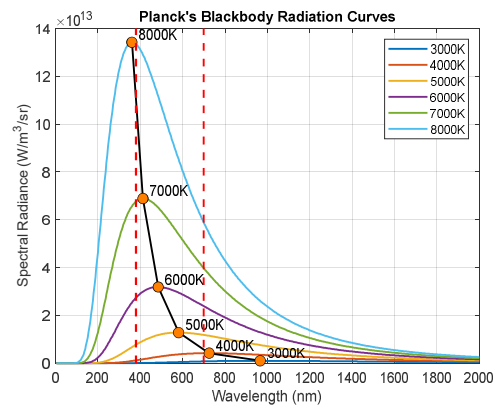


Figure 1 Planck's law for a blackbody at different temperatures highlighting the visible spectrum boundaries (vertical red dashed lines) plotted in MATLAB.

There are two types of modes in which thermographic inspection can take place. These are the active and passive modes. While the passive modes capture the inherent thermal behaviour of an object, the active mode makes use of a thermal excitation source to heat the specimen. Within the active mode the positioning of the IR camera and the heat sources is also an important factor for inspection. Figure 2 shows the two configurations which are known as the reflection and transmission modes.

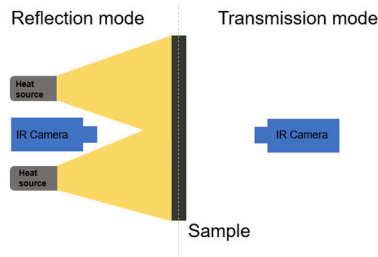


Figure 2 Active thermography in the reflection and transmission configurations.

In the reflection mode the heat source and the IR camera are placed on the same side of the specimen whereas in the transmission mode they are placed on the opposite sides of the specimen. It is important to mention here that while the figure above shows flash thermography as an example, the reflection and transmission modes can be applied to any form of active heat source such as a hot air gun, a halogen lamp and a laser source. A list of the various forms of active thermography types can be found in [14].

As mentioned previously infrared thermography has applications over a wide range of industries. Thus, it comes as no surprise that IRT has a big share in the NDT market. According to one report it is estimated that by the year 2032 the global projected value for the thermal imaging market is expected to be around \$14.02 billion [15].

IRT also offers a wide range of image and signal processing algorithms that enhance raw thermographic data. These include Thermographic Signal Reconstruction. (TSR)[16], Pulsed Phased Thermography [17], and Principal Component Thermography (PCT) [18] to name a few.

While there has been significant development in various aspects of IRT, the technique still lags other NDT techniques such as UT. One of the main reasons for this is that other methods such as UT and radiography are better at detecting defects that are buried deeper into the specimen compared to thermography. For example, a study published in 2014 by Maierhofer et al. showed that the detection capabilities of IR thermography significantly deteriorates when the defect is deeper than 3mm from the surface of the component in the reflection mode [19]. While the same study did reveal that the transmission mode can detect deeper defects, the depth quantification becomes a challenge. This is based on our current understanding of pulsed thermography as this is due to fact that the distance travelled by the thermal wave in the defect and defect free areas is the same [20]. To overcome this issue, other types of thermography such as lock-in has been used [21]. However, it must be noted that the inspection time is longer as a good understanding of the techniques response to excitation frequency is required beforehand thereby reducing the overall reliability to detect all types of defects.

With the emergence of new technologies and concepts like artificial intelligence, decentralised decision making, and digitalisation, fundamental changes to the entire IR inspection process are being made from the IR sensing material to image processing to give an assessment of the observed components overall structural health. The next section of this paper discusses some of the state-of-the-art in thermographic inspection, highlighting the current trends in this field.

3. Current state-of-the-art in IR thermography

3.1. Design of an inspection system

Recent studies have harnessed AI for inspecting and diagnosing composite material defects via thermography [22]. The existing AI research in related fields mainly conduct pulsed thermography experiments in the reflection mode. Neural networks built by machine learning algorithms have the potential to assist operators in processing thermal imaging data at a faster pace [23]. The process of IRT combined with machine learning approach is illustrated in Figure 4.

Initially, thermographic data is extracted from samples using an active thermography system. This data is then reconstructed into a format suitable for analysis. Subsequently, fundamental features for machine learning are extracted using algorithms. These features are fed into a supervised learning neural network, such as a Fully Connected Network (FCN), or alternatively, unsupervised learning frameworks like Deep Neural Network (DNN) are employed for effective data analysis to yield the final inspection results. Based on the complex interpretation of thermal data by the machine learning models, the condition and integrity of the sample are reflected.

3.2. Fully Convolutional Network (FCN)

Fully Convolutional Network (FCN) has the characteristic ability to accept input images of any size. It uses deconvolution layers to up-sample the feature map from the last convolution layer, restoring it to the same size as the input image. This process generates a prediction for each pixel while retaining the spatial information of the original input image. Subsequently, pixel-wise classification is performed on the up-sampled feature map, resulting in an output image that is marked with feature regions. This approach aligns well with the initial intentions of non-destructive testing and the operational methodology of thermographic non-destructive testing [24].

3.3. Automatic data process.

One of the core features of Industry 4.0 is automation. Tasks done manually in the previous industrial revolutions can now be accomplished

automatically with technologies that have emerged during the fourth industrial revolution. While automated decision making has been used in various industries it has seen limited progress especially in the context of IRT. One such instance can be seen in a study conducted by Duan et al. [25] where a two-multilayer feed-forward neural network model was used which was trained on defects created by different sources. The simulated sources were air, water, and oil. The results showed that the recall rate can exceed 97%. It also showed that the recall rate was better when using TSR (96%) when compared to using raw data (89%).

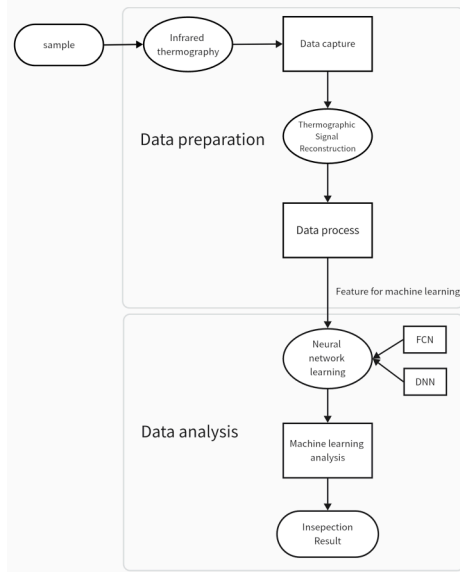


Figure 4 Process flow of non-destructive Testing combined with machine learning approach

Another example of machine learning being used in thermography is demonstrated by Zhou et al. [26]. In the study, 100 samples were produced based on various impact energy levels. The researchers then developed a pattern recognition method to understand the uncertainties associated with the damage contours. Figure 3 shows the contour band overlay for different plates for different impact energy levels.

3.4. Digital Twin

Digital twin technology can be defined as “dynamic digital representation of a real entity” [27]. Utilizing technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics, this can encompass all elements of its real-world counterpart. Sensors collect real-time data of the physical entity in the real world, allowing for the real-time updating of the virtual model's status and performance.

Currently the application of digital twins in thermography is very limited [28], [29]. However, it has been effective in the thermal analysis-based

tracking of food lifecycle and micro-simulation of electric vehicle energy consumption and range [30]. By simulating a continuous multi-physical field

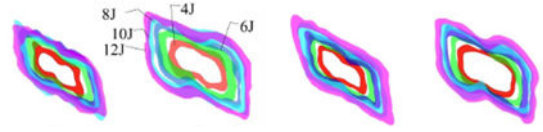


Figure 3 Damage contours for different impact energies [26]

model of objects, based on energy conservation, thermal boundary conditions, and the inherent properties of the simulated object, the lifecycle of the object being simulated is constructed [31].

Similarly, by combining the results of active thermal imaging data over the entire lifecycle of the test object with machine learning and Internet of Things (IoT) technologies, it's possible to track the conditions under which defects in the test object occur. Establishing a Digital Twin based on the lifecycle of the test object in its application environment to achieve traceability in maintenance holds potential.

4. Gap analysis

Recent years have seen significant growth in infrared technology. However, there are still some limitations that need to be addressed so that the full potential of the technique can be realised. These limitations can arise from uncertainties throughout the numerous aspects of IRT. These include uncertainties from the equipment, the inspection process, material type, the signal processing algorithms, and various environmental factors.

4.1. Theoretical and Numerical Modelling

One of the current standards of measuring the thermal diffusivity of materials is the flash method introduced by Parker et al. in 1961 [32]. In this method, Parker used small optical flash which dissipated 400 joules of energy in an order of milliseconds to thermally excite the material and recorded the temperature data at the backwall. Then the half rise time i.e., the time it takes the temperature to reach half the maximum temperature, as measured from the samples backwall was used to calculate the thermal diffusivity. The method is commercially available in instruments such as the LFA 427 [33]. However, there have been limited studies improving on this model since then [34], [35]

While there have been several numerical models for thermography in the reflection mode, there are no models showing the transmission mode. In the well documented reflection mode, the defect appears as a thermal hotspot due to the reduced rate of thermal decay in the defect area when viewed from the front wall. For the transmission mode however,

this should result in a cold spot as the heat in the defect zone would take longer to reach the back wall when compared to the defect-free zone. To the authors best knowledge, no study has recreated this effect numerically. The images in Figure 5 have been generated using the heat transfer study in COMSOL showcasing the thermal hotspot and cold spot respectively for a steel sample subjected to a flash heating of 6kJ for a duration of 2ms. The image is taken 2.12s after the flash. It can be clearly seen that the hotspot at the front wall caused by a delay in thermal decay translates to a cold spot at the back wall as the heat is reaching the backwall at a slower rate. The defects are highlighted using red circles.

Currently, depth quantification in through transmission pulsed thermography remains a challenge. There has been limited effort explaining this phenomenon. A recent conference paper by the authors took a numerical approach towards understanding this problem [36]. It showed that the temperature contrast between the defect and defect-free zones is more sensitive to lateral defect dimensions such as radius or length compared to the depth of the defect. This indicates that the difference in temperature does not offer a sufficient signal-to-noise ratio (SNR) to distinguish between the depths of defects.

4.2. Sensor limitations

The type of temperature sensing material in the infrared radiometer plays a crucial role in determining the resolution, accuracy, and temperature range of the instrument. Some of the current drawbacks in infrared images is the image calibration where due to the lens and the angle of the radiation, the images can appear to be distorted. While there are numerous image calibration algorithms for digital images, infrared image calibration algorithms are very limited. The most accurate method was introduced by ElSheikh et al. [37].

4.3. Image processing algorithms

While there have been many algorithms to process thermographic data, most of them have been developed for the reflection mode. There are limited algorithms for the transmission mode. This has negatively impacted the further development of the technique which has shown to detect deeper defects.

4.4. Integrating state-of-the-art technologies with IRT

While industry 4.0 has been around for a while, integrating the available technologies with infrared thermography has seen limited applications compared to other NDT techniques.

Of the above-mentioned limitations, all of them can be overcome by combining them with machine learning, artificial intelligence, and robotics to create

more complex simulations and image stabilisation algorithms. In terms of defect detection current researchers tend to focus on one type of defect to assess their proposed approach. With the advent of technologies and concepts such as Big Data and generative AI, more dynamic assessments can be made in terms of its structural health. Furthermore, it can lead to more accurate estimations of the remaining useful life (RUL) of components. Lastly, thermographic potential can possibly be fully realised with the central themes of Industry 4.0 where automated decisions can be made regarding a component that undergoes thermographic inspection.

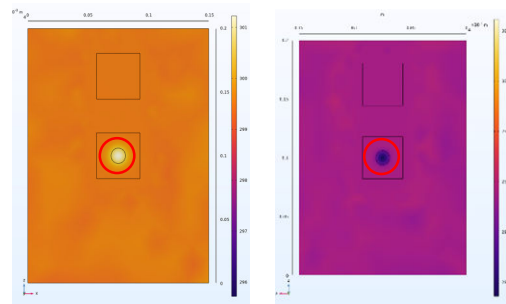


Figure 5 Thermal hotspot at the front wall (left) and the subsequent cold spot at the back wall (right)

5. Conclusion

While IR technologies have been limited due to several fundamental limitations, these limitations can be better understood by using concepts such as AI and digitalisation. This will also help in providing better insights on how to overcome these limitations and lead towards a greater appreciation for its potential. Current technology allows for viewing and addressing the limitations throughout the thermographic inspection process from the theory to the post processing of data. It will also allow IR thermography to cement its position as a powerful NDT technique that not only detects a fault but can also deliver suggestions on what the next steps should be post inspection. The authors also acknowledge that this study provides a preliminary analysis of the current drawbacks of IR thermography. There is a need for a full systematic literature review to provide a more comprehensive analysis of the current-state-of-the-art.

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