

Enhancing fault characterisation in composites using infrared thermography: a bee colony optimisation approach with self-organising maps

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ABSTRACT

This work presents an innovative approach aimed at enhancing the characterisation of discontinuities through the processing of thermographic images. The proposed methodology combines self-organising maps (SOM) with bio-inspired parameter optimisation through bee colony optimisation technique. The primary focus is on improving the quality of the fault quantification metric known as the signal-to-noise ratio (SNR). The goal is to achieve a better fault visualisation, ultimately contributing to the advance of thermography as a non-destructive technique. To validate this novel approach, an experiment was conducted using pulsed thermography on a unidirectional carbon laminate piece measuring 33 × 100 mm. This specimen was intentionally equipped with three artificial delaminations positioned at different depths on specific layers. The results were then compared against conventional approaches such as principal component analysis, partial least-squares regression and polynomial approximation. The findings from this experiment demonstrated the potential of the proposed approach, i.e. the bee colony optimisation coupled with SOM, on the characterisation of discontinuities using infrared thermography data. There was a 15% improvement on the SNR when using the proposed approach over the other tested approaches. This research makes a noteworthy contribution by offering a promising technique for both the detection and characterisation of faults in composite materials.

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1. Introduction

Several industry and other productive sectors rely on mechanical systems for their processes, making the monitoring of these systems essential to prevent catastrophic failures [1, 2]. In critical safety systems, damage detection is even more crucial due to human integrity. However, mapping the structural integrity of

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a physical system is a complex task, sometimes making it difficult to locate, quantify, and estimate its lifespan [3–5].

Various methods for detecting discontinuities in a system without impairing its future usefulness are available, including eddy current, ultrasonic inspection, computed x-ray tomography, and infrared thermography. These methods are classified as non-destructive testing techniques. Infrared thermography is able to identify damage non-invasively by analysing temperature variations through thermographic images, comparing various time intervals [6].

To perform the inspection, NDT systems use thermal cameras to measure thermal variations. These cameras are electronic optical devices used to detect and measure radiation and relate it to surface temperature. By inspecting the evolution of thermal variations on the surface of the analysed object, it is possible to identify surface and sub-surface discontinuities [7, 8]. However, environmental and operational factors can lead to false decisions about the structural integrity condition [9, 10].

To address these challenges, machine learning techniques such as artificial neural networks (ANNs) have been combined with NDT methods. ANNs are computational models inspired by the human brain, composed of interconnected layers of nodes (neurons) that process input data to recognise patterns and make decisions. There are several studies that have applied ANNs to identify damage using ANN models [4, 11–13].

While ANNs are effective at pattern recognition, they differ from modern deep learning neural networks (DLNNs) in their structure and capability. DLNNs, a subset of ANNs, contain multiple hidden layers, enabling them to automatically learn hierarchical features from the data without manual feature extraction. In contrast, traditional ANNs typically contain fewer layers and rely more on feature engineering performed by human experts [13].

The main advantage of ANNs over DLNNs lies in their simplicity and computational efficiency, especially when applied to smaller datasets or when the problem does not require the deep, hierarchical feature extraction that DLNNs provide. DLNNs, with their deeper architectures, require larger datasets and more computational resources but can outperform ANNs in tasks involving complex data, such as image recognition and natural language processing. However, ANNs remain a solid choice when computational resources are limited or when the complexity of the data does not justify the use of a deep architecture Vavilov2020.

Bioinspired optimisation methods have been developed to support machine learning algorithms, reducing human influence in model construction [14–16]. These methods are inspired by natural processes and behaviours observed in biological systems, such as the collective behaviour of ants, the foraging patterns of bees, or the evolution of species. For instance, Ant Colony Optimisation (ACO) mimics the way ants find the shortest path to food by using pheromone trails, while Bee Colony Optimisation (BCO), applied in this work, simulates the decision-making process of bees when searching for nectar. These algorithms explore the solution space more efficiently than traditional methods, optimising complex problems with multiple variables.

In the context of structural health monitoring and damage detection, bioinspired methods help to enhance the performance of machine learning models by fine-

tuning parameters such as network topology and learning rates, while also reducing the likelihood of overfitting. This optimisation ensures that the model is robust and can generalise well across different data sets. The integration of bioinspired methods with neural networks, like the one proposed in this study, offers a powerful approach to detect structural discontinuities, as it automates the search for optimal solutions, minimising human intervention [16].

In this work, we propose an approach that combines Kohonen Self-Organizing Maps (SOM) with a bioinspired optimisation method based on bee colonies (BCO) to determine the best neural architecture to maximise the characterisation of structurally artificially inserted delaminations in a 33×100 mm carbon-fibre reinforced polymer (CFRP) flat sample. To the best of our knowledge, BCO has never been applied in thermographic data before. The optimisation results and SOM network demonstrated the effectiveness of the proposed approach when comparing the signal-to-noise ratio (SNR) of the artificial delaminations to results obtained with principal component analysis, polynomial approximation, and partial least square regression, showing their applicability in detecting discontinuities in composite materials through infrared thermography [5].

2. Fundamentals

2.1. Infrared thermography

Infrared Thermography (IRT) is a non-destructive, non-intrusive, and contactless technique considered relatively fast compared to other forms of radiation testing, without impairing the future use of the inspected object [17]. In passive IRT, the object under inspection typically has a temperature different from its surroundings, and this difference is captured by an infrared camera for instance. This technique is widely used in surveillance and medical applications [18, 19]. On the other hand, in active IRT, the object under inspection is in equilibrium with the surrounding environment, and an external stimulus source is used to either heat or cool the object, typically applied in monitoring of structures and mechanical systems [20]. The generated temperature differences are then monitored by an infrared camera, resulting in a sequence of images used for object assessment.

2.1.1. Pulsed thermography

The most used active IRT method is pulsed thermography (PT), where the sample's surface is subjected to a heat pulse using a high-power source, such as photographic flashes. After the thermal front makes contact with the sample's surface, a thermal front travels from the surface through the sample. Over time, the surface temperature uniformly decreases for a flawless part (e.g. solid area). On the other hand, subsurface discontinuities (e.g. porosity, delaminations, displacements, and fibre breakage) can be considered as barriers to heat flow, producing abnormal temperature patterns on the sample's surface. This abnormal temperature distribution can be detected with an infrared camera (IR) [3–5]. [Figure 1](#) shows the schematic configuration of PT in reflection mode where camera and heating source are placed at the same side of the inspected sample. A synchronisation unit is

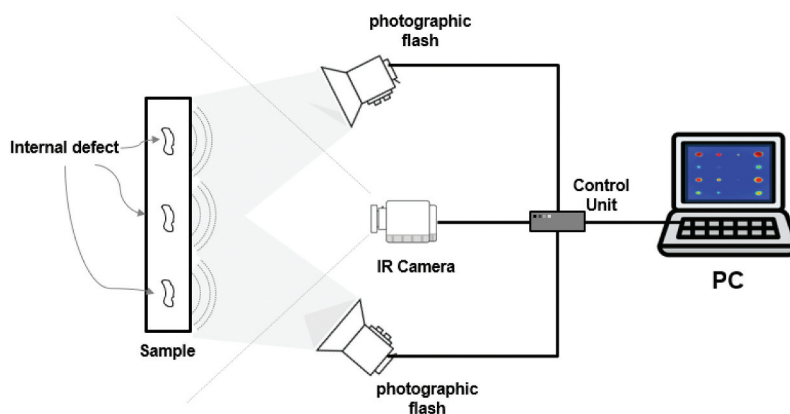


Figure 1. Schematic configuration of PT.

required to control the timing between the thermal pulse release and recording with the IR camera. PT is fast, direct and is the most used active IRT method

However, to achieve better qualitative results and meaningful quantitative ones, one must perform data processing algorithms due to the physical nature of the heat transfer phenomena in solids. Next, the specific data processing methods used in this study are described.

2.2. Infrared image processing

The application of image processing techniques in thermographic images aims to quantify and improve the characterisation of faults. It is widely used since such methodologies ensure the applicability of the technique in various structures. In this work, four different algorithms are used. The first is based on principal component analysis and is called Principal Component Thermography (PCT). In PCT, the data sequence is decomposed into a set of orthogonal statistical modes (known as Empirical Orthogonal Functions or EOFs) obtained through Singular Value Decomposition (SVD). The most significant information is concentrated in the first EOF images [21, 22].

The second algorithm is a polynomial approximation approach that creates synthetic data based on the real experimental data. The polynomial approximation is a widely used technique that reduces the spatial and temporal resolution of a sequence, thereby reducing the amount of data to be analysed. There are complexities in processing images captured by PT, which can be resolved by transforming the problem domain into a logarithmic domain [17–23].

The third algorithm used is called Partial Least Squares Regression (PLSR). It reconstructs obtained thermal sequence during the inspection into a new sequence of images less contaminated by noise while maintaining physical coherency. With PLSR, it is possible to link time and temperature data, in a similar manner as in the polynomial approximation allowing the extraction of the most important variations while discarding unnecessary information present in the original thermal sequence. PLSR decomposes the raw thermal data into multiple PLS components, each component being orthogonal to each other.

Since each of the PLS components is characterised by its variance, it is possible to identify different phenomena affecting the overall thermal regime through the PLS components [6].

The last algorithm explored in this study is called Self-Organizing Maps (SOM). This is an artificial neural network that abstracts high-dimensional data and is applied to colour quantisation with the goal of reducing the distinct colours used in a given image to make the new image visually as similar as possible to the original image [24]. SOM have been applied for years now in different domains including NDT [25] and passive IRT [26, 27]. However, to the best of our knowledge, it has not yet been fully explored in active IRT. Recently, Schwedersky et al. [28] used SOM to segment low-energy impact damages in CFRP samples using Optical lock-in thermography and square-pulse shearography images. However, in this study, the architecture of the SOM is not automatically optimised using bio-inspired algorithms. The use of processing techniques in conjunction with SOM networks in the colour quantisation of thermographic images aims to find an optimal colour combination to enhance fault characterisation.

2.3. Quantitative analysis of processing

To assess the quality of the data processing method to evaluate the faults, qualitative analyses of the images are performed after the processing step, comparing the images at each stage of the processing along with the assessment of a metric, the Signal-to-Noise Ratio (SNR).

SNR describes the differences between a defective area and a non-defective area, establishing a dynamic range. In other words, for each defect, an area located in the defect, called the signal area ($Sarea$), and an area around (or near of) the defect, called sound area representing the noise related to defect's signal, are selected. There are several formulas to calculate the SNR. In this study Equation 1 is applied to obtain the SNR values [29]:

$$SNR = \frac{S}{N} = 20 \cdot \log_{10} \left(\frac{abs(Sarea_{mean} - Narea_{mean})}{\sigma} \right) [db] \quad (1)$$

where $Sarea_{mean}$ is the mean pixel values for the defect, $Narea_{mean}$ is the mean pixel values in the defect-free region (sound area) considered and σ is the standard deviation of the pixel values in the defect-free region.

2.4. Self-organizing maps

Kohonen self-organising maps (SOM) are a special type of artificial neural networks that are used to abstract high dimensional data and, therefore, can be applied to various types of problems and fields of study [15]. In this sense, SOM neural networks use unsupervised learning so that, by adjusting a two-dimensional grid of nodes, it is possible to delimit the topological representation of input data to a lower dimension [15]. Strictly speaking, Kohonen maps can be described through the adoption of an M_{xy} mesh of nodes, which can be a rectangular, hexagonal, or even irregular mesh. Each node, in turn, describes

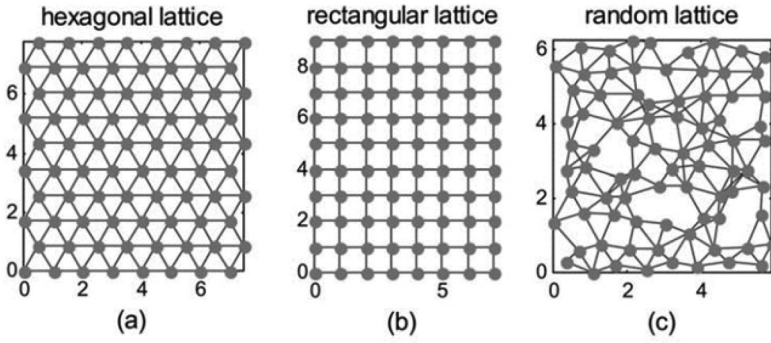


Figure 2. Mesh types adopted in SOM. Adapted from [30].

a Cartesian position (x, y) of one of the network's neurons. Figure 2 shows some of the possible mesh configurations adopted by a Kohonen self-organising map.

Initially, the SOM network neurons are assigned a weight vector $w_i \in \mathbb{R}^T$ (where $i = 1, 2, \dots, n$) of random values, with i representing the index of the neurons and k representing the dimensionality of the input space. During the iterations of the network training process, these weight values are adjusted as they are presented to the input vectors x_i (where $i = 1, 2, \dots, n$), which are k -dimensional input vectors of the problem. Here, i ranges from 1 to n , where n is the total number of neurons in the SOM network, while k refers to the number of features (or dimensions) in the input data, determining the size of the input vector. The values of i and k depend on the size of the dataset and the dimensionality of the problem being addressed.

In the literature, batch competitive learning procedures are generally used to carry out the training process of SOM maps. Thus, the training algorithm is formulated so that the inputs are connected to all neurons of the network and, at each iteration, small comparisons of the distances between these inputs and the respective synaptic weights of the neurons are made [15, 31]. Among the main equations used to calculate the weight distance of a SOM network, the formulation of the Euclidean distance is a very common one, which can be expressed as Equation (2).

$$d_i = \|w_i - x_i\| = \sqrt{\sum_{i=1}^n (w_i - x_i)^2} \quad (2)$$

Considering the competitiveness relationship among the network neurons, it is possible to estimate the one with the best match for each input, and this procedure is performed according to Equation (3).

$$\text{BMU}_k = \arg \min(d_i) \quad (3)$$

where BMU stands for Best Matching Unit, representing the position of the best weight vector associated with the current input vector x_{ik} . With the delimitation of the competing neuron, the process of adjusting the network weights begins. For this, the input values x_i

are then used to correct the synaptic weights close to the winning neuron, using a function h_{ck} , which is called a neighbourhood function [15, 31].

Equation 4 represents the correction adopted by the neurons close to the competing neuron k , while Equation 5 describes the neighbourhood function (Gaussian exponential) commonly used in studies of self-organizing maps.

$$w_i(t+1) = w_i(t) + h_{ck}(t) \cdot |x_{ik} - w_i(t)| \quad (4)$$

$$h_{ck}(t) = \alpha(t) \cdot e^{\left(\frac{-\|BMU_k - r_{kj}\|^2}{2\sigma^2(t)}\right)} \quad (5)$$

where t is an integer value that describes the current iteration of the algorithm, α is a representative value of the learning rate, σ is a factor that describes the neighbourhood radius to be considered, and $\|BMU_k - r_{kj}\|$ represents the distance of each neighbouring neuron r_{kj} in relation to the current competing neuron BMU_k .

Observing Equations 4 and 5, one can see that for those neurons further away from the competing neuron, the value of $h_{ck}(t)$ will be smaller and, therefore, the adjustment will be less efficient for these neurons. The procedures for choosing the Best Matching Unit neurons and the respective correction of the other network neurons are repeated at each iteration of the training process. Such conditioning results in network convergence, thus shaping the Kohonen map characteristic of the input data topology [32].

Furthermore, as a numerical method, a stopping criterion must be adopted in the formulation of the SOM network training algorithm, which can vary concerning the maximum number of iterations, processing time, minimum tolerance value, and others. It is also worth noting that the low dimensionality resulting from the SOM network processing allows the data to be diagrammed on a two-dimensional map, which can be easily interpreted by humans.

2.5. Bee colony optimization

Bee Colony Optimization (BCO) is a bioinspired optimisation method developed by [33], designed to tackle complex combinatorial problems.

The basic idea of the method is to mimic certain natural behaviours of bees building a population P of multi-agent candidates, where each agent (represented as a bee in the population) determines a possible solution to the problem under study.

In the literature, there are various conceptual lines that have been and still are used in the development of BCO algorithms. These lines are directly related to the natural behaviours of bees, such as food collection, mating, and/or cooperation with the queen bee by other bees in the population. It is important to note that BCO is originally formulated as an unconstrained global minimisation problem and can be adjusted to accommodate penalties and constraints typical of engineering problems.

The problem addressed by BCO can be formally expressed as the identification of a parameter vector x_i that minimises a given objective function $f(x_i)$, as given by Equations 6 and 7:

$$\min f(x_i), \quad x = (x_1, x_2, \dots, x_n) \in S^n \quad (6)$$

where:

$$l_{s_i} \leq x_i \leq u_{s_i}, \quad i = 1, \dots, n \quad (7)$$

In this context, l and u represent the lower and upper bounds of the design variable x_i in the n -dimensional search space S with n dimensions or variables.

Assuming a formulation based on food collection to define the feasible solution to the problem, BCO first randomly defines an initial population of bees. Each solution vector, i.e. food location, defined by these bees is evaluated in terms of its fitness and suitability for solving the problem.

From there, a search process, known as mutation, for new solutions is initiated using a subset of bees from the population P called exploratory bees. The goal of exploratory bees is to identify new food locations, i.e. values of x , that minimise the objective function $f(x_i)$.

After the new candidates food locations are determined, the algorithm initiates another population remapping process, known as crossover, in which exploratory bees share their information with another subset of bees which are also chosen randomly.

These bees, called spectators, perform a probabilistic selection process to find the best food region for the current population and adjust their positions based on the fitness relationships provided by the exploratory bees. The selection procedure used by the spectator bees is commonly defined in the literature as Roulette Wheel Selection and is given by Equation (5) [34]:

$$p_i(x_i) = \frac{\text{fit}(x_i)}{\sum_i \text{fit}(x_i)} \quad (8)$$

It is important to note that due to the collective iterations (inherent in the mutation and crossover processes of the candidate population) among the bees, the search behaviour for viable solutions tends to converge towards a cooperative intelligence format, where bees focus on the most promising solution areas and gradually abandon less promising regions of the search space. In Algorithm 1, the BCO algorithm we use is presented, and in the following, its underlying approach is described in detail.

The main steps of the BCO algorithm are as follows:

- Initialisation: A population of artificial bees is initialised with random solutions.
- Employed Bee Phase: Each employed bee searches for a new solution in the neighbourhood of its current solution.
- Onlooker Bee Phase: Onlooker bees select solutions based on the quality of the solutions found by employed bees and search in their neighbourhood.
- Scout Bee Phase: If a solution does not improve for a certain number of iterations, the bee becomes a scout and searches for a new random solution.
- Termination: The algorithm terminates when a stopping criterion, such as a maximum number of iterations or a satisfactory solution quality, is met.

Algorithm 1 provides a detailed pseudocode representation of the BCO algorithm used in this work, illustrating the sequence of operations and decision-making processes that enable the bees to optimise the search for solutions effectively.

Algorithm 1: Bee Colony Optimization (BCO) Algorithm

Result: Optimised solution for the given problem

Initialisation: Initialise a population of artificial bees with random solutions;

while *stopping criterion not met* **do**

Employed Bee Phase;;

for *each employed bee* **do**

 Search for a new solution in the neighbourhood of the current solution;

 Evaluate the fitness of the new solution;

if *the new solution is better* **then**

 Replace the current solution with the new solution;

end

end

Onlooker Bee Phase;;

 Calculate the selection probability for each solution based on its fitness;

for *each onlooker bee* **do**

 Select a solution based on the calculated probabilities;

 Generate a new solution in the neighbourhood of the selected solution;

 Evaluate the fitness of the new solution;

if *the new solution is better* **then**

 Replace the selected solution with the new solution;

end

end

Scout Bee Phase;;

for *each bee that has not improved for a certain number of iterations* **do**

 Abandon the current solution and search for a new random solution;

end

end

In this work, the BCO Algorithm 1 is applied to optimise the hyperparameters of the SOM Network that was applied as the last processing step in 6 different data processing configurations which are detailed in the next section. The thermographic data processing techniques used in this work were PCT, TSR and PLSR. By optimising the SOM Network parameters, damage detection in inspected structures is improved, leading to more accurate and reliable results. This ensures that improved techniques are better suited for identifying and characterising failures, ultimately increasing the effectiveness and reliability of thermographic inspections.

The combination of IRT with SOM and BCO is particularly valuable because IRT generates large, complex datasets that require sophisticated processing techniques to identify defects effectively. SOM helps to structure and reduce the dimensionality of the thermographic data by creating a topological map, which allows for the identification of meaningful patterns related to structural integrity. However, the performance of SOM is highly sensitive to the choice of hyperparameters, such as learning rate and network size, which, if not optimised properly, can lead to poor generalisation or overfitting. This is where BCO provides a significant advantage.

By applying the BCO algorithm to optimise SOM's hyperparameters, it is possible to systematically search for the best configuration without relying on manual trial and error. BCO mimics the behaviour of bee colonies to explore the solution space more efficiently, leading to better parameter selection, which enhances the SOM network's ability to identify damage in thermographic data. The advantage of combining SOM and BCO lies in the automation and precision it brings to the damage detection process, resulting in more accurate detection of defects, with minimal human intervention. This combination improves the overall reliability and robustness of thermographic inspections.

3. Methodology

In order to test the proposed approaches, a PT experiment was conducted for this work. A flat Carbon Fiber Reinforced Polymer (CFRP) laminate, with three artificial inserts, manufactured with carbon/PEEK (Polyether Ether Ketone) APC-2/AS4, containing a 61% volume fraction of fibre with a $[0_2/90_2]_6$ layup was inspected. The laminate sample measures 100 X100 mm, as shown in Figure 3, and the region considered in the study, highlighted in the figure, corresponds to a 33X100 mm section in the top of the image.

In Table 1, the thermal properties of APC-2/AS4 are listed. Moreover, the positions of the defects inserted in the sample are shown in Figure 4. The nominal depths of the defects are 0.13 mm for D1, 0.26 mm for D2, and 0.39 mm for D3. The artificial Kapton tape inserts, all of the same size (4 X 4 mm), were placed at these specific depths (D1, D2, and D3) and in different layers during the moulding process.

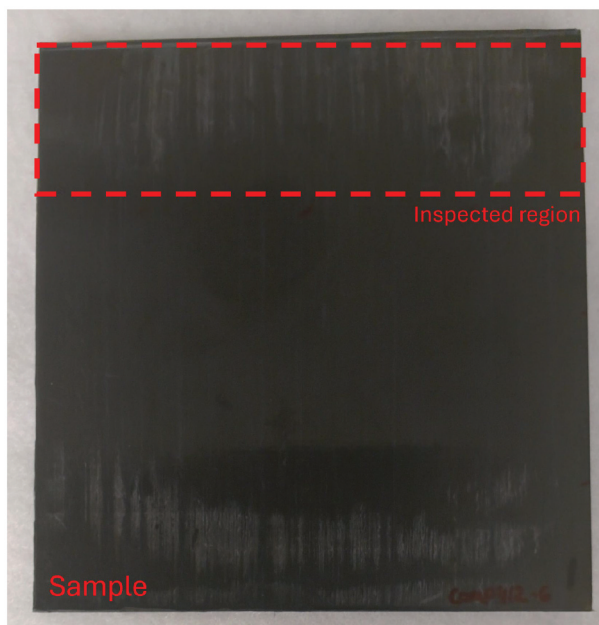


Figure 3. Sample and the region inspected.

Table 1. Thermal properties of APC-2/AS4 [35].

Property			Value	
k :	Thermal conductivity	Longitudinal	5.65	[W/mK]
		Transverse	0.35	[W/mK]
C_p :	Specific heat ^(a)		1310	[J/kgK]
ρ :	Density		1584	[kg/m ³]

^aat constant pressure.

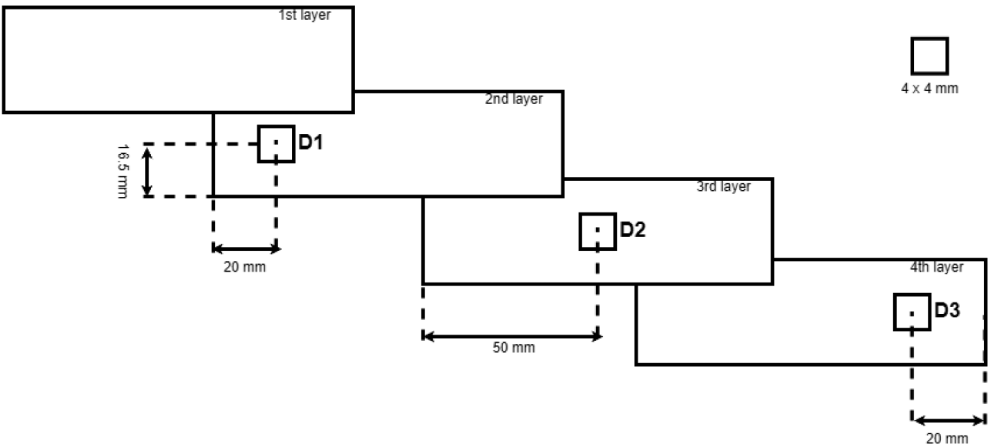


Figure 4. Location of defects in the sample. Defect 1 (D1), Defect 2 (D2), and Defect 3 (D3).

The configuration used for the experiment is shown in Figure 5. The camera used was a FLIR Phoenix, InSb, 3-5 μ m, with a resolution of 640 $\times$ 512pixels. The camera frame rate was 55 hz, with a 5 ms photographic pulse, producing 6.4 kJ of energy per flash for sample heating, and the recording was done in reflection mode. The camera was about 1.5 m from the sample and the flashes about 1.0 m from the sample. Three samples can be seen in Figure 5, however, for this study, only the sample in the centre was considered. Images were acquired for 25 seconds resulting in a sequence containing 1385 images.

Subsequent steps of reading, processing, and evaluation were applied to the data, all of which were carried out using the Python programming language. Figure 6 shows the steps involved in the methodology applied in this work.

Prior to the data processing approaches, the so called cold image, i.e. an average image calculated from all images in the sequence before the flash pulse, was subtract from all the image in the sequence. This is usually done to reduce noise and remove unwanted reflections in the data sequence. Figure 7 shows the selected regions used to evaluate SNR.

Next, 10 different processing configurations were applied to evaluate the new proposed methodology through SNR and qualitatively. Explored configurations were:

- Configuration 1: Raw images. The 5 5ms after the flash pulse was evaluated.
- Configuration 2: PCT processed images. The second EOF was evaluated.
- Configuration 3: PLSR processed images. The second load was evaluated.

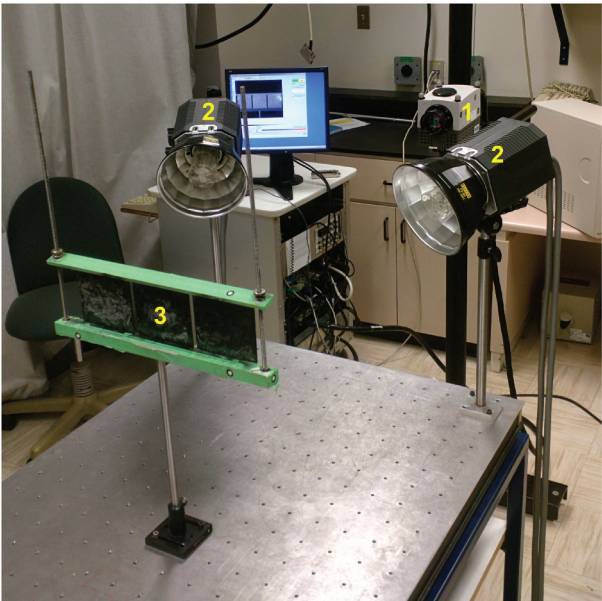


Figure 5. PT set-up used: 1. Infrared camera, 2. Flashes, and 3. Inspected sample.

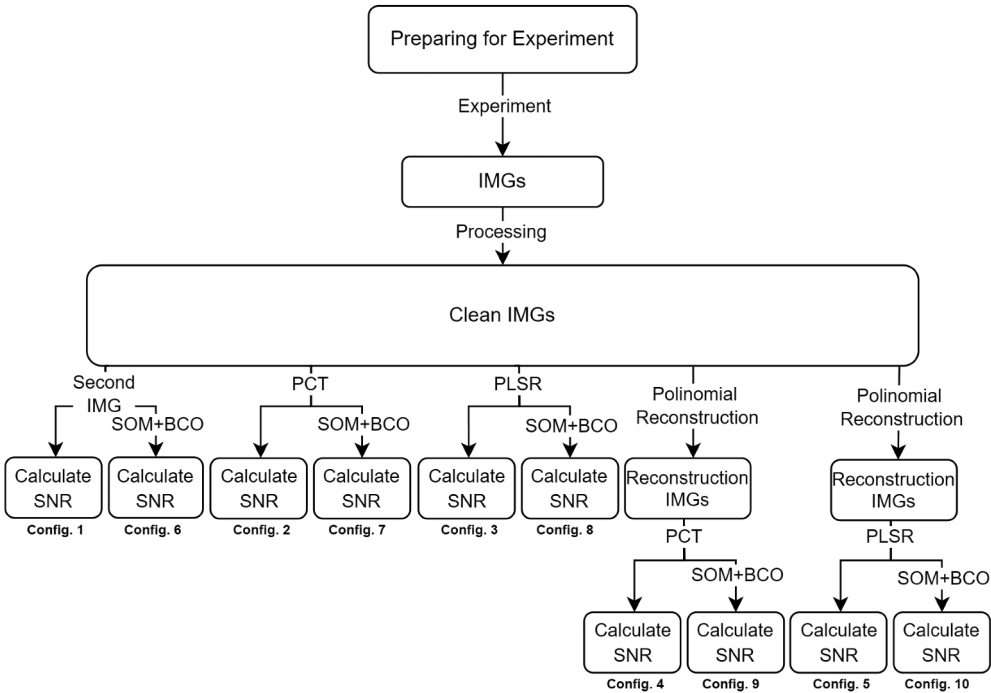


Figure 6. Steps of methodology applied.

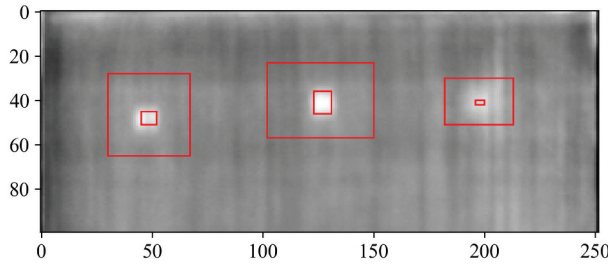


Figure 7. Selected defect regions and respective sound regions for SNR analysis.

- Configuration 4: Polynomial fitting followed by PCT processing. The second EOF was evaluated.
- Configuration 5: Polynomial fitting followed by PLSR processing. The second load was evaluated
- Configuration 6: SOM processed images with network parameters optimised with BCO. The image at 5 ms was evaluated.
- Configuration 7: Configuration 2 results were applied with BCO. The second EOF was evaluated
- Configuration 8: Configuration 3 results were applied with BCO. The second load was evaluated.
- Configuration 9: Configuration 4 results were applied in conjunction with SOM + BCO.
- Configuration 10: Configuration 5 results were applied in conjunction with SOM + BCO.

For Configuration 6 to 10, the bee colony optimisation (BCO) algorithm was employed to identify an optimal set of hyperparameters for the Self-Organizing Map (SOM) network. The primary goal of the SOM quantisation model was to maximise the Signal-to-Noise Ratio (SNR) across all three types of defects simultaneously. This maximisation of SNR was critical for enhancing the resolution and clarity of defect detection in the resulting images.

In this context, the objective function of the BCO algorithm was experimentally developed to optimise the SNR for all three types of defects at the same time, ensuring that the algorithm prioritises configurations that improve the visibility and distinction of all defects. Equation 9 presents the equation developed and used as a multi-objective function that considers all possible faults and negatively weights the total solution in case there is a fault with negative SNR, i.e. the noise region is more prominent than the fault.

$$Objective = \sum SNRs - 2 \times \max(-1 \times SNRs, 0) \quad (9)$$

where $SNRs$ is the list of SNRs calculated in the specified regions, and the $\max$ function returns the greater value between the list of SNRs and 0.

The choice of this objective function was necessary due to the nature of the optimisation problem, that is, it seeks to find the solution that maximises the SNRs and, if it does not consider all the SNRs, the method will try to improve the easiest failure and disregard the others. By considering all the SNRs, we achieve a uniform result for all possible failures.

The training of the SOM network uses an RGB image as input in each iteration of the optimisation, which will be improved by quantisation. For example, in configuration 1, the raw image is used in the training. In each iteration of the optimisation, a new training is performed on the same image, allowing the search for the best combination of hyperparameters.

The parameters adjusted during the SOM network optimisation included the colour map range ($x[15 \text{ to } 25]$ and $y[15 \text{ to } 25]$), a fixed learning rate of 0.5, which was kept fixed considering the default value of the hyperparameter defined by the author of the package used and commonly used in the literature, and the effective spread between neighbouring neurons on the map, which ranged from 2 to 10 neurons. Additionally, different map topologies (rectangular and hexagonal) and neighbourhood functions (Gaussian, triangle, Mexican hat, and bubble) were explored [36].

In the BCO, a vector containing parameters (x , y , neighbourhood function, topology, effective spread) represented each possible configuration. The algorithm utilised a population of 15 bees, with 5 observer bees, and the optimisation process continued until either 10 iterations were completed or the standard deviation of the population cost of the objective function fell below 0.0001, this value was defined by observing the decays of the cost in a separate run with 200 iterations using a configuration 1 where the SNR has good values starting from 0.0001.

Figure 7 shows the selected regions used to evaluate SNR, providing a visual representation of the areas focused on during analysis. The SNRs calculated for each configuration provided a quantitative measure of the image quality concerning defect resolution. The evolution of the bee colony algorithm was evaluated to assess the effectiveness of each configuration in enhancing defect detection, considering both the overall SNR improvement and the qualitative appearance of the quantised images.

The selection of the noise and signal regions was defined in order to guarantee the greatest representation of each region, that is, for the noise region, the edge of temperature changes was identified for its selection. For the noise region, the largest possible region was selected in order to provide representation for both the signal surroundings and for the very different regions surrounding the signal. This ensures that the method can be used in the most diverse conditions.

4. Results

The proposed methodology, i.e. SOM optimised with BCO, showed improvements both quantitatively, increasing the SNR value, and qualitatively, making the analysed defect region clearer compared to the defect-free region as it can be seen in Figure 8. Table 2 compares the SNRs for the 10 proposed configurations.

To complement the quantitative analysis, a qualitative evaluation of the improvement in the quality of the defect in the thermographic image was performed for the configuration that resulted in the highest sum SNR, i.e. Configuration 9. Figure 10 presents the qualitative assessment between Configuration 4 and Configuration 9, which are the best results achieved while all numerical results are shown in Table 2. Additionally, the method using PLSR also showed good performance, achieving an SNR very close to that of PCT, confirming that PLSR can be an effective method for enhancing the detection and characterisation of defects in thermographic images.

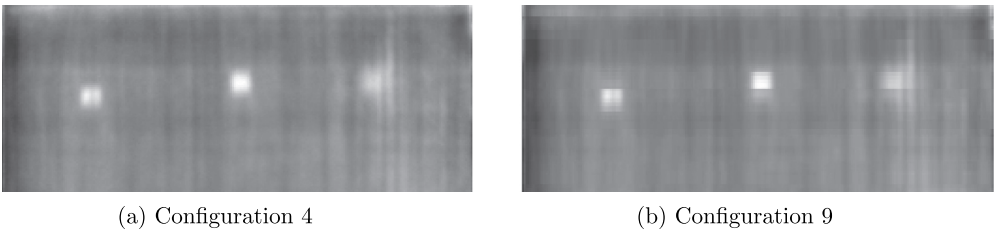


Figure 8. Qualitative comparison.

Table 2. SNR results from each tested configuration.

Configuration	SNR			
	D1	D2	D3	Sum
1	25.52	7.8	−20.85	−29.23
2	24.82	22.05	11.09	57.96
3	24.77	22.19	11.38	58.34
4	24.7	22.35	11.95	58.99
5	24.8	22.4	11.90	59.10
6	11.15	1.63	−7.75	−10.47
7	25.01	22.95	11.65	59.61
8	25.07	22.96	11.62	59.66
9	25.09	23.2	12.7	60.99
10	25.07	22.92	11.58	60.89

A critical factor influencing optimisation results is the number of search iterations. The study employed a 10-iteration search, leading to a progressive improvement in the overall SNR by 1 dB (decibels) with each iteration. The detailed progression of SNR enhancement across all 10 iterations is illustrated in Figure 9.

In Figure 9(a), a decrease in SNR for fault 2 in IMG processing is revealed, starting from the second iteration. This can be attributed to the inherent low quality of the image data for this particular fault, introduced during the moulding process of the part. However, all other iterations exhibited progressive SNR improvements.

In Figure 9(b), the optimisation evolution for Configuration 7 is shown. Unlike Configuration 6, all three faults (D1, D2, and D3) exhibit higher initial SNR values. Fault D1,

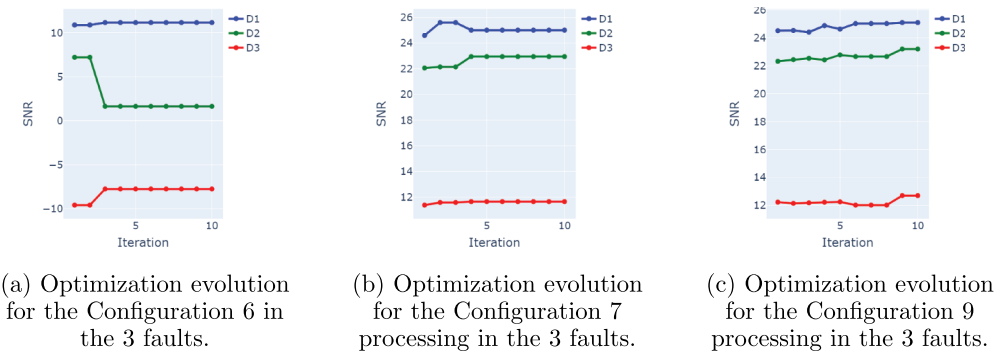


Figure 9. Analysis of the optimization evolution for each processing.

in particular, shows a notable increase, starting at approximately 22 dB and stabilising around 25 dB after the first few iterations. This improvement is likely due to the better quality of the processed image data compared to Configuration 6. Despite this, fault D3 remains stable with a significantly lower SNR, around 12 dB, indicating it remains more challenging to detect in this configuration.

Figure 9(c) presents the optimisation evolution for Configuration 9, where all faults achieve significantly higher SNR values compared to Configurations 6 and 7. Fault D1 reaches approximately 25 dB, while fault D2 stabilises at around 24 dB, showing the impact of improved optimisation techniques in this configuration. The most significant difference is seen in fault D3, where the SNR slightly increases after the third iteration, reaching about 13 dB. This improvement over previous configurations highlights better detection, although D3 continues to exhibit the lowest SNR.

These findings demonstrate the effectiveness of the combined approach utilising Principal Component Transform (PCT) processing and the optimised Self-Organizing Map (SOM) network in enhancing both the SNR value and the quality of defect visualisation within the thermographic image.

Overall, the significant differences in SNR between Configurations 6, 7, and 9, particularly for faults D1 and D2, demonstrate progressive improvements in defect detection. Configuration 9 consistently shows the highest SNR across all faults, with differences in dB reaching up to 10 dB compared to Configuration 6.

5. Conclusion

In this work, a novel approach to thermographic image processing utilising Self-Organizing Maps (SOM) with bioinspired optimisation techniques to enhance fault characterisation has been successfully proposed and validated. The outcomes of the proposed approach, juxtaposed with conventional methods, exhibited quantitative improvements in terms of defect SNR.

Moreover, the application of bee colony optimisation for the first time in thermographic data has showcased remarkable efficacy in optimising the SOM parameters, thereby enhancing fault detection and characterisation. Additionally, the integration of Partial Least Squares Regression (PLSR) and Principal Component Thermography (PCT) methodologies has proven to be instrumental in improving the Signal-to-Noise Ratio (SNR) of the images, further enhancing the diagnostic capabilities of the proposed approach.

The approach embraces a multi-objective optimisation strategy, considering all types of faults comprehensively to ensure a holistic analysis. This methodology acknowledges the diverse nature of defects that can occur in materials, allowing for a more robust and inclusive evaluation. Additionally, the evaluation is extended to encompass all timestamps, thereby analysing the entire spectrum of thermographic images. This thorough temporal analysis enhances fault detection by capturing variations and transient characteristics that might otherwise be missed in a limited timeframe. Furthermore, the research explores the efficacy of alternative bioinspired algorithms, utilising the versatility and adaptive capabilities of bioinspired optimisation techniques. This exploration aims to advance thermographic image processing, potentially uncovering new avenues for improving defect detection accuracy and reliability.

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Data availability

Data is available upon request.

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