**Surface defect characterization and depth identification of CFRP material by laser line scanning**

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***Abstract*:** The detection of defects on the surface of carbon fiber reinforced polymer has increasingly become the focus of modern NDT research. In this paper, the shape characterization and depth identification of surface defects of CFRP materials are investigated by establishing reflective and transmissive line laser infrared thermography nondestructive inspection systems. First, we verified the feasibility of the work by simulation. Then, the temperature variation of surface defects was analyzed by two experimental schemes, reflective mode and transmissive mode. To characterize the shape of the defects, we deduced the size of the detect from the scan of the line laser. The results show that the characterization accuracy of defect size is different for different scanning speeds, and finally the characterization error can be controlled within 2.2%. In order to achieve the defect depth classification, we used the gray wolf optimization algorithm to optimize the hyper-parameters in the support vector machine, which can finally achieve 97% depth classification accuracy in 0.56s.

***Keywords:*** Shape characterization; Depth identification; CFRP; Hyper-parameters search; Support vector machine (SVM).

|  |  |
| --- | --- |
| **Abbreviations** |  |
| CFRP | Carbon Fiber Reinforced Polymer |
| NDT&E | Non-Destructive Testing and Evaluation |
| NDT | Non-Destructive Testing |
| LIT | Laser Infrared Thermography |
| LST | Laser Spot Thermography |
| LLT | Laser Line Thermography |
| LSTM-RNN | Long Short Term Memory Recurrent Neural Network |
| SVM | Support Vector Machine |
| PSO | Particle Swarm Optimization |
| GA | Genetic Algorithm |
| LS-SVMs | Least-Square Support Vector Machines |
| CS | Cuckoo Search |
| GS | Grid Search |
| LMC | Lumber Moisture Content |
| GWO | Grey Wolf Optimizer |
| CV | Cross-Validation |
| RBF | Radial Basis Function |
| RS | Random Search |

1. **Introduction**

Nowadays, carbon fiber reinforced polymer (CFRP) are increasingly used in aerospace [1, 2], rail transportation [3, 4], bridges [5, 6] and medical devices [7, 8] which is mainly due to its high mechanical and electrical performances. As the application of CFRP becomes more and more widespread, its safety needs more and more attention. To meet the needs of assembly connections, CFRP materials usually require secondary processing, such as drilling and trimming, and other traditional processing methods; in addition, fiber laser cutting is a promising and efficient processing method. When focused laser beam impinges on the surface of the workpiece, a certain amount of heat is absorbed by the material at the surface and was subsequently conducted into the workpiece, where thermal defects can arise in the process, such as the presence of micro-cracks, cavities and striations on the surface of the material [9-11]. The surface damage forms and texture direction of milled surfaces of carbon fiber reinforced plastics were analyzed by Cai et al [12]. Pejryd et al. evaluated the surface integrity of drilled holes in CFRP composites by X-ray computed tomography (CT scan) [13]. Relevant detection technologies have been introduced. Non-destructive testing and evaluation (NDT&E) can provide basic information on surface and internal damage of composite materials, and is an effective tool for quantitative assessment of defects and damage and analysis of damage behavior. Non-destructive testing (NDT) such as infrared thermography [14], ultrasonic inspection [15], X-ray [16] and acoustic emission [17] play an important role in the inspection of composite materials. Due to the advantages of non-contact and high detection efficiency, infrared thermal imaging has become increasingly popular among engineers. Infrared thermography is a relatively new method in nondestructive testing and evaluation. It is divided into active and passive thermal imaging [18]. Methods for active infrared thermography require thermal excitation of the tested object, which has already played a significant role in detecting defects and in production quality control. There are many excitation heat sources for infrared thermography, such as laser [19], halogen lamp [20], eddy current [21] and ultrasonic [22]. Depending on the shape of the heat source, we can divide the scanning method into point scanning and line scanning. The line optical heat source uses a narrow line of heat flux and the thermal gradient is generated by scanning the heat flux across the surface of the object at a constant speed [23], which can significantly reduce the defect detection time compared to point scanning. Researchers often use halogen lamps, quartz lamps and inductive line heat source as the line optical heat source for heating [24-27]. Thermography using a laser as a heat source is known as laser infrared thermography (LIT). More and more researchers are using LIT to measure the depth and size of defects of CFRP materials. Chen et al. used image processing techniques to determine the location and size of defects, and this method allows for automatic identification of defects [28]. Wei et al. used laser array scanning thermography to detect subsurface defects in carbon fiber reinforced composites [29]. Wang et al. investigated the feasibility of differential spread laser infrared thermography to detect delamination and impact damage in CFRP [30]. According to the scanning method, we can classify LIT into laser spot thermography (LST) and laser line thermography (LLT). The laser heats one point at a time on the surface of the sample and spreads the area to be inspected by a point-by-point scanning method, which is called LST. In our previous work, we performed in depth prediction and characterization of metal surface defects by the LST [19, 31, 32]. LLT can significantly reduce defect detection time and can achieve satisfactory detection results [33, 34]. LLT can quickly detect the distribution of defects on the surface of the sample. And similar to LST, the temperature at the defect will be different from the surrounding temperature during the laser scan sweeping over the defect [19].

According to the relative position of the heat source and the infrared camera, infrared thermography non-destructive testing technology can be divided into two types: reflective mode and transmissive mode. In the reflective mode, energy is delivered to the specimen from the same side from which data are recorded; in the transmissive mode, energy is delivered to one side of the specimen while observing from the opposite side.

In recent years, researchers have carried out studies on the classification of depth of surface defects of sample parts. Jiang et al. acquired and trained the characteristic information of different rail defects by support vector machine (SVM), and achieved efficient and high accuracy rail detection by the input of features during the detection process [35]. Marani et al. first extracted new features of analytical significance from the thermally normalized signal and classified them using several machine learning methods [36]. Duan et al. used neural networks in infrared thermography to classify defects, such as air, oil, and water, which can degrade material performance [37]. Hu et al. proposed an infrared thermography-based NDT technique and a long short term memory recurrent neural network (LSTM-RNN) model which automatically classifies common defects occurring in honeycomb materials [38]. In our previous work, we used neural architecture search for the first time to classify metal surface defects and achieved excellent classification accuracy [19]. We also propose a derivative analysis method to quantify the depth of metal surface defects, which can control the accuracy of quantifying the depth of defects to within 7% [31]. In addition, we perform hyper-parameters search by grid search and random search for KNN, SVM and random forest, thus achieving depth classification of steel plate surface defects [32].

The classification of defect depth starts with obtaining the information of the tested sample containing defects by NDT methods, and then classifying and identifying the defects by building classifiers. These classifiers include numerical fitting, conventional machine learning methods and deep learning methods. To improve our previous work, this study proposes to classify defects at different depths on the surface of CFRP sample by constructing machine learning classifiers.

SVM [39] is a common discrimination method which can help to quickly evaluate the objective function with high predictive power and good generalization performance for a limited number of samples. In the field of machine learning, it is a supervised learning model, usually used for pattern recognition, classification and regression analysis. Due to the simplicity of its classification idea, it has been widely used by a large number of researchers in various fields, and the field of non-destructive testing is no exception. Liu et al. proposed a SVM-based pipeline defect signal extraction and identification method, which can achieve accurate classification of the damage degree of pipeline defects [40]. Ankush et al. combined IRT with SVM to classify faults in bearings [41]. Zou et al. proposed a novel intelligent diagnosis method for classifying different states of electrical equipment using a combination of infrared image data and SVM [42].

In order to optimize the SVM algorithm to better solve problems in various domains, the hyper-parameters need to be tuned to obtain the best model structure [43]. In recent years, researchers have been optimizing the hyper-parameters of SVM by various optimization algorithms to solve the problems encountered in industrial production. Li et al. used particle swarm optimization algorithm (PSO) to obtain penalty factor *C* and kernel parameter *g* of SVM model to improve the performance of cable-stayed bridge surface defects classification [44]. Genetic algorithm (GA) was used to optimize the parameters of SVM. Experiments show that this optimization algorithm can identify and classify flip chips quickly and accurately [45]. To solve the problem of not being able to diagnose the internal insulation defects of oil-impregnated paper bushings in detail, Wang et al. proposed a multiclass least-square support vector machines (LS-SVMs) based method optimized by the cuckoo search (CS) algorithm to diagnose the internal insulation defects of oil-impregnated paper bushings [46]. Zhang et al. used grid search (GS) techniques to optimize support vector machines for regression and prediction. Experiments showed that the GS-based support vector machine classification method showed better performance in solving lumber moisture content (LMC) measurement and prediction problems [47].

It has been shown that searching for hyper-parameters in SVM through optimization algorithms can accelerate the speed of solving problems encountered in industrial production. Grey Wolf Optimizer (GWO) algorithm is an intelligent algorithm based on the social behavior of wolves. The basic idea is that according to the social hierarchy characteristics, wolves of *alpha*, *beta* and *delta* totaling three leadership levels search and locate the prey, and guide wolves *omega* to track and capture the prey [48]. We introduce the GWO-based SVM algorithm for the first time to address the identification of defect depths on CFRP surfaces.

1. **Workflow**

We divided the study into three stages to identify the depth of defects on the CFRP surface. Data acquisition is the first step. We built the optical path to convert the point laser into a line laser to scan the CFRP samples with surface defects. An infrared thermal imaging camera was used to obtain the surface temperature variation of the CFRP samples. Feature extraction is the second step.Compared to classifiers, feature engineering can determine the accuracy of defect depth recognition more. Finally, we optimize the hyper-parameters in SVM with GWO to build a defect depth classifier, and then compare it with two hyper-parameters optimization algorithms, random search and grid search. We achieve the depth recognition of CFRP surface defects. Fig. 1 represents the workflow of this paper.



**Fig. 1.** The workflow of this paper.

1. **Theoretical foundation**
   1. *Heat Conduction Theory*

For the temperature rise induced by the laser source in homogeneous, isotropic and semi-infinite materials, the three-dimensional heat conduction can be expressed as [49]:

 (1)

where *T* is the temperature rise. *K* and *k* are respectively the thermal conductivity () and diffusivity (m2/s). Their relationship is: .  is the density of the material (*kg/m3*), and *C* is the specific heat of the material ().  is the heat produced per unit volume per unit time, in unit of W/m3.

The instantaneous temperature rise from a line source [49] is:

 (2)

where  is the energy per unit length in the line heat source (J/m). *r* is the radius in a polar coordinate (pole is the point source center).

A continuous heat source has the same effect as a sequence of a very large number of small instantaneous sources of equal size. Thus, for a point source with continuous heating and when *Q* is constant, the integrated temperature result in the time domain is [49]:

 (3)

where *q* is source power (W)

For a line source with continuous heating, the integrated temperature result in the time domain is [49]:

 (4)

where  is source power per unit length (W/m).

* 1. *Support Vector Machine (SVM)*

SVM is a machine learning method based on statistical theory proposed by Vapnik et al. in the 1990s that can efficiently handle nonlinear classification and regression problems. The method is based on the principle of structural risk minimization by mapping the input vector to a high-dimensional feature space through a nonlinear mapping, and finding the optimal regression hyperplane in this space that minimizes the objective loss function, which is expressed as:

 (5)

where, *w* is the weight coefficient matrix; *b* is the threshold;  is the mapping function; *x* is the support vector.

The SVM search for the optimal hyperplane process ensures smooth functional relationships by minimizing the sum of squares of the weight coefficients; errors less than  are tolerated by solving the following quadratic convex programming problem to determine *w* and *b* :

 (6)

The constraints are:

 (7)

where,  are the relaxation variables; *C* is the penalty factor, *C>0*;  is the allowable error; *xi* is the *i*th sample vector; *yi* is the output value of *xi*.

* 1. *Grey Wolf Optimizer (GWO)*

The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature which was first proposed in 2014 by Mirjalili et al [48]. Four types of grey wolves such as *alpha*, *beta*, *delta*, and *omega* are employed for simulating the leadership hierarchy. The GWO algorithm consists of three main steps: encircling prey， hunting prey and attacking prey. The encircling prey can be expressed by (8) and (9).

 (8)

 (9)

where the position of the *i*th grey wolf, the current iteration and the position of the prey are denoted by *xi*, *t* and *xp*. The vectors *A* and *C* are control parameters that are calculated by (10) and (11).

 (10)

 (11)

where *r1* and *r2* are random vector in [0, 1], and a is linearly decreased from 2 to 0 over the course of iterations computed by (12).

 (12)

To mathematically model the hunting behavior, it is supposed that the leader wolves can estimate the possible position of the prey; therefore, the whole of the omegas would be guided by three-leader *alpha*, *beta*, and *delta* wolves. The position of each *omega* wolf *xi* is updated by:

 (13)

 (14)

 (15)

 (16)

 (17)

 (18)

 (19)

1. **Experimental setup and sample data**

The schematic diagram of the experimental setup in this study is shown in Fig. 2. We used a semiconductor laser as the heat source with a central laser wavelength of 915 nm and the laser power was set to 6W with continuous excitation. The water cooling unit cools the working laser to ensure its proper operation and prevent safety failures. The optical path combination of a flat convex lens and a flat convex cylindrical lens adjusts a point laser with a diameter of 400μm to a line laser with a length of 40mm and a width of 2mm. The CFRP sample containing the defects is mounted on a moving platform. As the platform moves, the linear laser can scan the entire CFRP sample. In the experiments, the distance between the laser source and the CFRP specimen is 1m, and the angle between the infrared thermal imaging camera and the laser is 13°. The distance between the CFRP sample and the IR camera is close enough that it is almost assumed that the atmospheric transmittance is 1 and does not cause much error. The setup in the experiment can be seen in Fig. 3.



**Fig. 2.** Diagram of the experimental setup.



**Fig. 3.** Experimental setup.

The CFRP specimen was laid in only 0° layers, and the number of layers was 14. In order to simulate CFRP surface pore defects, we machined circular holes with depths of 0.5mm, 1mm, 1.5mm and 2mm, respectively, and diameters of 5mm on the surface of CFRP T800 material with the thickness *D* of 2.4mm. Fig. 4 shows the schematic diagram of the CFRP sample structure.



**Fig. 4.** The schematic diagram of the CFRP specimen structure. *d1*, *d2*, *d3* and *d4* denote 0.5mm, 1mm, 1.5mm and 2mm depth defects respectively;  denotes the diameter of the defect.

1. **Experimental results**
   1. *Data Analysis and Shape Characterization*

In our previous work, we have detected metal surface defects with pulsed laser excitation and IR camera to capture the temperature change within 2s after heating [19]. The feasibility of extracting IR features to classify the depth of defects in a short time was verified. In this paper, in order to study the heating and cooling process of IR images within 6s, we scanned the CFRP sample containing defects by a line laser and observed the temperature change. To observe the line laser scanning process, infrared images were acquired every 0.5s.

Firstly, to verify the feasibility of the work, we build a finite element numerical simulation model using COMSOL Multiphysics. The parameters of the model are shown in Table 1. Fig. 5(a) shows the simulation model established. Fig. 5(b) shows the infrared images after laser scanning with the temperature variation of the point *G* near the defect. We can see that the temperature of point *G* rises from the ambient and is highest when the laser sweeps through point *G*. Then the temperature gradually decreases.

**Table 1**

Parameters setting of CFRP.

|  |  |
| --- | --- |
| Parameters | Value |
| Specific heat capacity (*J/*(*kg·K*)) | 754 |
| Thermal conductivity (*W/*(*m·K*)) | 35 |
| Density (*kg/m3*) | 1600 |
| Laser power (W) | 6 |



(a)



(b)

**Fig. 5.** Simulation verification.

We set the laser scanning speed to 1.3 mm/s, 2.6 mm/s, 3.9 mm/s and 5.2 mm/s to investigate the effect of different scanning speeds on the detection results. Although the setup parameters are the same, the infrared images obtained by the IR camera are different due to the difference in scanning speed. Fig. 6 shows the infrared images of the laser after sweeping through the defect at depth = 0.5mm in reflective mode. We can see in Fig. 6(a) that the defects in the swept area are the most visible when the laser moves at a speed of 1.3 mm/s, and two defects can be observed. As the speed increases, the defect away from the laser becomes blurred. This is because the slower the heat source moves, the longer the time for heat to act on the surface of the CFRP material, resulting in a higher temperature on the defect surface. When the depth of the defect is the same, the delay time of heat transfer is the same. However, since the heat generated by the laser on the material surface is different at different sweeping speeds, the higher the energy of the laser acting per unit area, the higher the temperature of the defect surface will be, i.e. the slower the speed of the heat source, the higher the internal temperature. The above reasons lead to the phenomenon in Fig. 6. The average value of the defect temperature for the depth of 2mm was extracted and the normalized temperature change over 5s was plotted , as shown in Fig. 7. We can see that the larger the scanning speed, the more pronounced the temperature change. This is because when the recording time is the same, the larger the scanning speed, the further the defect is from the laser source, which makes the temperature drop larger. In this paper, we do not need to make the defect visible even after moving away from the laser. Rather, we need to sweep the surface of the sample containing the defect efficiently and quickly. In addition, the high surface temperature caused by the slow speed is likely to damage the sample. Therefore, we finally set the scanning speed of the laser to 5.2mm/s.



**Fig. 6.** Infrared images at different scanning speeds. (a) scanning speed = 1.3mm/s; (b) scanning speed = 2.6mm/s; (c) scanning speed = 3.9mm/s; (d) scanning speed = 5.2mm/s.



**Fig. 7.** The average of the temperature variation of the 2mm defect depth after normalization.

In order to study the surface temperature variation after line laser scanning of the sample. Two experimental modes were used, reflective mode and transmissive mode. In the reflective mode, the laser beam, the infrared camera and the defect are on the same side; in the transmissive mode, the infrared camera is on the same side as the defect and the laser beam shines on the other side. Infrared thermal images of defects with depths of 0.5 mm and 2 mm were studied for 1s after laser sweeping through the defects.

Fig. 8(a) shows that in reflective mode, the temperature of the defect is significantly lower than the surface temperature after the line laser sweeps over the defect for 1s at a defect depth of 5mm. The circular area in Fig. 8 indicates the defect. This indicates that the heat transfer within the surface defect (depth = 0.5mm) of the CFRP material is significantly faster than the surrounding surface temperature after 1s of heating. When the defect depth is 2mm, the temperature of the defect is significantly higher than the surrounding surface temperature, as we can observe in Fig. 8(b). This indicates that the deeper the defect depth, the longer its corresponding delay time, which leads to sufficient heat transfer to the defect surface after 1 s, when the temperature of the CFRP surface above the defect is in the decreasing stage, thus leading to the phenomenon that the defect temperature is higher than the surface temperature in Fig. 8(b). In conclusion, in the reflection mode, deeper defects produce longer delay times.

In the transmissive mode, the surface temperature at 1s can be represented in Fig. 8(c) and (d). The defect depth in Fig. 8(c) is 0.5mm. The difference between the temperature of the defect and the surface temperature is not significant, and the location of the defect can not be clearly determined by the human eye in the infrared image. When the defect depth is 2mm, the temperature of the defect is significantly higher than the surrounding surface temperature, as we can observe in Fig. 8(d). Because the deeper the defect, the closer the bottom surface of the defect is to the heated surface of the material, the temperature can be transferred to the bottom surface of the defect for a short time *ta*. It leads to a higher temperature on the bottom surface of the defect than on the backing surface. On the contrary, when the defect is shallow, the longer time *tb* is needed for the heat transfer. Fig. 9 explains how the delay time leads to this phenomenon. So in the transmissive mode, the delay time of temperature transfer leads to the difference between the defect temperature and the surrounding temperature. We can clearly observe the difference between the defect temperature and the surrounding temperature in the line temperature diagram in Fig. 8. Also because of the delay time, in the reflective mode, we can clearly observe the shape of the line laser; while in the transmissive mode, the exact position and shape of the laser can not be observed.



(a) (b)



(c) (d)

**Fig. 8.** Surface temperature of CFRP material using reflective and transmissive modes. (a) indicates defect depth=0.5mm, reflective; (b) indicates defect depth=2mm, reflective; (c) indicates defect depth=0.5mm, transmissive; (d) indicates defect depth=2mm, transmissive.



**Fig. 9.** Delay time in heat transfer.

Fig. 10 shows the variation of the material surface temperature in the reflection mode. As can be seen from the figure, the temperature inside the defect gradually increases as the laser approaches the defect, but since the thermal conductivity inside the defect is smaller than that of the surface material and time delay exists in heat transfer, the warming process is said to be less pronounced than that of the surrounding surface. When the line laser is directed above the defect, the temperature inside the defect increases significantly. As the laser moves away from the defect, the temperature at the defect will show a decreasing trend. However, the temperature will be higher than the surrounding temperature. As we can see in Fig. 10, there is a clear trailing phenomenon on the surface when the laser sweeps over the sample. Defects are clearly visible in the trailing area.

Fig. 11 shows the difference in temperature between point *A*, the center of the defect, and point *B*, which has a horizontal distance of 6mm from it. From the figure, we can see that the temperature difference between points *A* and *B* can be up to 60℃. From the time the line laser sweeps over the defect, the temperature at the defect is always higher than the temperature of the sample around it.

To better observe the location and shape of defects, we binarized the IR images. The threshold value is set by us artificially. We take the example of laser sweeping over the defect for one second. We set the threshold values of 0.7, 0.385, 0.368 and 0.33 for infrared images with defect depths of 0.5mm, 1mm, 1.5mm and 2mm, respectively. Fig. 12 shows the effect of the binarization. We can see that the circular defects can be shown in the figure and the position can be well reflected. This can verify that the continuous laser scanning platform we built can detect the specific location of the defects on the surface of the CFRP sample.



**Fig. 10.** Temperature sequence diagrams; point *A* indicates the temperature of the center of the defect; point *B* indicates the temperature at a horizontal distance of 6mm from point *A*.



**Fig. 11.** Temperature difference between point *A* and point *B.*

Quantifying the size is an important step after locating the defect. We binarized the adjacent 0.5s IR images and then superimposed the two images. Fig. 13 shows the results of the processing. We can see that the binarized image will show trailing phenomenon. Also the defects will be partially overlapped. *D* is the size of the defect diameter observed after binarization. The diameter of the defect in the infrared image can be determined by calculating the size of the pixel grid occupied by ** and *D*, as in (20):

 (20)

where  and  denote the pixel sizes occupied by  and *D*, respectively.



**Fig. 12.** Binarization of infrared images with different defect depths.



**Fig. 13.** Infrared image overlay effect at 0.5s interval (scanning speed = 5.2mm/s).

For different laser scanning speeds (1.3mm/s, 2.6mm/s, 3.9mm/s and 5.2mm/s) we used this method to quantify the size of the defects separately. Table 2 shows the results of the quantitative analysis. The accuracy of dimensional characterization can reach up to 97.8%. We can see that the accuracy of the defect diameter characterization is improving as the moving speed increases. Theoretically, this method is able to accurately derive the true defect size. There are two reasons for this phenomenon, the first is that the thermal imaging camera does not capture the infrared image pixels very well; the other point is that when the thermal imaging camera captures the moving sample, the image in the direction of movement will exist vignetting phenomenon. Eventually, the calculated defect diameter is not exactly equal to the real defect diameter.

**Table 2**

Calculation results of defect diameter.

|  |  |  |
| --- | --- | --- |
| Scanning speed | Calculated diameter | Error |
| 1.3mm/s | 4.10mm | 18.0% |
| 2.6mm/s | 4.25mm | 15.0% |
| 3.9mm/s | 4.45mm | 11.0% |
| 5.2mm/s | 4.89mm | 2.2% |

* 1. *Depth Classification*

For each defect, we repeat the measurement 20 times and feature extraction for it according to the method mentioned in the previous section; the hyper-parameters in the SVM are searched using the GWO method mentioned in the previous section and compared with the grid search and random search. In this work, we use the central temperature at the defect as the feature value. The infrared camera captures the temperature change of CFRP surface defects within 6s and records infrared images every 0.5s, such that each defect is feature by *F*=[*t1,t2,t3,…,t10,t11,t12*]. Due to the small sample size and to avoid overlearning and under-learning, we evaluate all methods using 3-flods cross-validation (CV) sample data, selecting 50% of the data for training and 50% for testing, and repeating 3 times to obtain 3 non-overlapping validation datasets. Finally, the average of the accuracies of the 3 experiments is the final experiment result. Subsequent experiments are conducted in this form.

The penalty factor *C* and the kernel parameter *g* are two important hyper-parameters in SVM that directly affect the classification effect. We search for these two hyper-parameters within a predefined range by the GWO algorithm. The pre-set parameters such as *C,* *g* and number of wolves are shown in Table 3.

**Table 3**

Parameter setting.

|  |  |
| --- | --- |
| Parameters | Value |
| Number of wolves | 5,10,15,20 |
| Max number of iteration | 10 |
| Number of parameter optimization | 2 (*C* & *g*) |
| Kernel function | RBF |
| Preset range of *C* & *g* | 0.01-10 |

First, we manually select the number of wolves in the GWO algorithm and preset the number of wolves to 5, 10, 15 and 20. the number of iterations is set to 10. Fig. 14 represents the variation of classification accuracy with increasing number of iterations when setting different numbers of wolf packs. We can see from Fig. 14 that the number of wolves does not affect the accuracy of the defect depth classification after 10 iterations, but it affects its convergence speed. The convergence is relatively slow when the number of wolves is 10, and the highest classification accuracy is reached only after the third iteration. When the number of wolves is 5, 15 and 20, the convergence rate is the same, and the highest classification accuracy has been reached after the second iteration. This is firstly due to the fact that the features we counted to select are more representative and a smaller number of wolves can achieve high accuracy defect depth classification. Another reason is that when the number of wolves increases, the wolves' decision will be more efficient and the decision speed will be faster. In addition, in order to choose the appropriate number of wolves, we compare the running speed of the algorithm with different numbers of wolves, as shown in Fig. 15. We can see that the running speed of the algorithm increases linearly with the increase of the number of wolves. In order to simplify the computation and shorten the defect depth classification time, we choose 5 as the final wolf number for subsequent experiments.



**Fig. 14.** Classification accuracy of SVM algorithm with different number of wolves.



**Fig. 15.** Classification speed of SVM algorithm with different number of wolves.

To verify the superiority of GWO algorithm, we compare it with random search (RS) and grid search (GS) optimization algorithms. The preset values of the experimental hyper-parameters are the same as before.

Table 4 shows the classification results after the optimization of SVM. From the table, it can be seen that the optimal results of classification are different when different kernel functions in SVM are chosen. When RBF is used, the accuracy of RS and GS based SVM is 87% and 85%, respectively. When hyper-parameters search is not used, the classification accuracy of the algorithm is only 70%; the classification accuracy of SVM based on GWO can be as high as 97%. In comparison, this method can improve the classification accuracy by 27%. Similarly, when Linear is used as the kernel function, the GWO-based SVM will have about 2% improvement in classification accuracy over the other two optimization algorithms. When Poly was used as the kernel function, all three hyper-parametric search methods yielded the same classification results, with a 2% improvement over not using hyper-parameters search. This is due to the fact that the poly kernel function has more parameters and is more computationally intensive. The search of the wolf pack is tedious when using the GWO method, which will lead to the classification effect is not effective at a smaller number of iterations. We can see that the penalty factor and kernel parameter *g* corresponding to the highest classification accuracy are different for any of the hyper-parameters search methods. Due to the high search efficiency of the GWO method, it can perform better in the same search range. We can also see from Table 4 that the running time of the program based on the GWO method will be longer, but the running time is less than 1s regardless of which kernel function is selected. We consider this to be acceptable for engineering applications.

**Table 4**

Classification results of different optimization methods.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Optimization algorithm | Accuracy | Time (s) | *C* | *g* |
|  | RBF | | | |
| Unoptimized  RS | 0.70  0.87 | 0.100560  0.108019 | 2.3539  2.3539 | 0.162  0.112 |
| GS | 0.85 | 0.131340 | 6.6184 | 0.300 |
| GWO | 0.97 | 0.560309 | 2.5953 | 0.117 |
|  | Linear | | | |
| Unoptimized  RS | 0.93  0.93 | 0.084633  0.094543 | 9.7157  9.7315 | 8.9819  2.9005 |
| GS | 0.93 | 0.086905 | 9.4089 | 0.0995 |
| GWO | 0.95 | 0.613750 | 0.1222 | 0.4261 |
|  | Poly | | | |
| Unoptimized  RS | 0.93  0.95 | 0.098655  0.138711 | 9.6535  9.3529 | 8.3405  4.7408 |
| GS | 0.95 | 0.091144 | 9.3300 | 4.8691 |
| GWO | 0.95 | 0.603529 | 0.0126 | 0.2862 |

1. **Discussion**

We established reflective and transmissive mode setups for CFRP surface defects. These setups are used to characterize the shape and identify the depth of defects on the surface of the sample. The feasibility of the idea was verified by simulation studies. In the simulation, we only studied the heat conduction and heat diffusion inside the sample and with the air, and did not consider the heat exchange between the surface of the sample and the ambient. However, it does not affect the integrity and realism of our work. In our future work, we will improve the simulation study by adding different factors affecting the heat transfer. There is a clear difference between the IR images acquired by reflective and transmissive CFRP surface defect systems. In this paper, we mainly analyze the IR images acquired by reflective mode setups, but we also cover the study of IR images of some transmissive mode setups. In the future research, we will further investigate these two setups for surface defect detection of CFRP materials.

In previous study, we explored the surface temperature variation of a stainless steel sample containing defects during 2s of point-shaped pulsed laser excitation. In this paper, we extend the acquired infrared image time series to 6s in order to explore the temperature variation of surface defects of CFRP materials, which greatly increases the surface cooling time, so that the temperature variation of defects during the cooling period can be better investigated. In the study of shape characterization, different laser scanning speeds affect the accuracy of dimensional characterization, and although this is partly due to the performance of the infrared camera, the characterization method proposed in this study does have the phenomenon that speed affects characterization accuracy. Therefore, in future work, we will further investigate how to improve the accuracy of dimensional characterization. We will research on the method of threshold selection when binarizing infrared images. In the study of defect depth identification, we only considered four kinds of defects with different depth sizes, and in future work we will prepare a variety of defects with different depths to study, so that it can be more in line with the practical application of engineering and provide better guidance for the depth analysis of CFRP surface defects.

We optimized the hyper-parameters of the SVM by the GWO algorithm and compared it with the unoptimized, RS-optimized and GS-optimized algorithms. Experiments demonstrate that applying the GWO algorithm to the depth classification of defects can achieve satisfactory results. However, the running time of the GWO procedure will be about 0.6s longer than that of the other algorithms, and we believe that the time difference, which is not yet one second, does not affect the efficiency of defect depth discrimination.

1. **Conclusion**

In this paper, the temperature variation of CFRP materials containing surface defects was investigated by establishing a reflective and transmissive line laser infrared thermography nondestructive testing systems. The feasibility of the work was first demonstrated by a simulation study. It was found that the shape characterization of surface defects in CFRP materials can be achieved by these systems. Experiments show that different scanning speeds have an effect on the characterization of defect shapes. When the scanning speed is 5.2mm/s, the accuracy of defect shape characterization can reach 97.8%. The depth discrimination of CFRP surface defects was also achieved by hyper-parameters optimization of the SVM classifier through the GWO algorithm. In the depth discrimination experiments, we investigated the effects of the number of wolves, the penalty factor *C* and the kernel parameter *g* on the defect depth classification. The explored method can achieve depth discrimination accuracy up to 97% within 0.56s.

**CRediT authorship contribution statement**

**Haoze Chen:** Investigation; Methodology; Writing – original draft. **Zhijie Zhang:** Writing – review & editing. **Wuliang Yin:** Conceptualization. **Quan Wang:** Data curation. **Yanfeng Li:** Software. **Chenyang Zhao:** Software.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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