A Comparison of Feature Extraction Techniques for Delamination of CFRP Using Eddy Current Pulse-Compression Thermography

X. Lu, Q. Yi, and G. Y. Tian

Abstract—CFRP (carbon fiber reinforced plastic) has replaced conventional metallic materials in many industrial applications because of its outstanding mechanical performance such as high strength to ratio and resistance of fatigue. During the service life of the aerospace composite component, delamination left without detection can cause a sudden breakdown of the structure. Eddy current pulse-compression thermography (ECPuCT) is an emerging technique that combines traditional ECPT and pulse compression techniques. In this work, feature extraction techniques of impulse response have been exploited in terms of principal component analysis (PCA), kernel principal component analysis (K-PCA) and independent component analysis (ICA). Each technique is evaluated using SNR as the index to compare their performance. The results indicate that Kernel-PCA performs better than PCA and ICA based features when dealing with delamination ranged from defect#1(0.46mm) to defect#9 (2.30mm).

Index Terms—CFRP, Eddy current pulse-compression thermography, kernel-PCA, ICA, SNR.

I. INTRODUCTION

Carbon fiber reinforced plastic as a kind of emerging composite material, has been used widely in many industrial applications, because of its remarkable performance such as high stiffness and low density. Thus, the integrity of CFRP under various loading conditions like impact loading is very critical for the structure. Delamination is one of the most common defects for CFRP, they mostly occur and grow between different layers of CFRP. The structure of CFRP with delamination has lower strength and stiffness, which may lead to the fragility of the overall structure [1]. Under these circumstances, regular quality testing of composite can eliminate potential hazards as far as possible [2].

Numerous Non-destructive testing (NDT) techniques were used in the CFRP delamination detection. Ultrasonic Testing technique was applied in the damage detection of CFRP, but its results are easily distorted by high frequency [3]. CFRP with barely visible impact damage (BVID) was inspected through vibrothermographic technique, this technique can be well combined with local defect resonance [4]. However, those techniques have drawbacks like complex equipment, time-consuming, and low immunity to external factors [5], [6].

Active Thermography (AT) was proposed to detect delamination of CFRP, it makes up for the shortcomings of traditional NDT techniques. AT can achieve a large range of one-time detection. Ultrasonic Testing technique was applied in the damage detection of CFRP, but its results are easily distorted by high frequency [3]. CFRP with barely visible impact damage (BVID) was inspected through vibrothermographic technique, this technique can be well combined with local defect resonance [4]. However, those techniques have drawbacks like complex equipment, time-consuming, and low immunity to external factors [5], [6].

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However, the defect detection of UST often suffered from problems like undesirable damage to the sample under test due to the contact between the sample and probe [10].

ECPT is an emerging AT technique in the NDT field, it performs effectively than conventional NDT technique in the detection of CFRP defects [11]. Besides, it has higher detection efficiency and in-depth capability, higher resolution than traditional eddy current because of the combination of multi-physics nature which contains Joule heating and heat diffusion [12]. In the ECPT system, a coil carried with high-frequency alternating current is used to excite eddy current inside the sample. The abnormal structure of surface and subsurface will change the distribution density of the eddy current, which leads to the irregularity of the thermal distribution observed by the infrared camera [13]. In previous works, the application of ECPT has been studied for detection and quantities of fatigue cracks, corrosion, and loading impact [14]. Since CFRP exhibits low electrical conductivity and layered structure the process can be considered volumetric heating. Depending on the eddy current frequency and the thickness of sample, the skin-depth is greater than the sample thickness [15]. The thermal distribution on the sample surface can be observed easily with a thermal camera, but artificial pixel-selection around defective area leads to different characterization results, thus faithful quantitative evaluation of the delamination depth from thermal response was obstructed [16]–[18].

To improve the detection capability of ECPT, the combination of pulse-compression (PuC) techniques and eddy current excitation was proposed as ECPuCT in recent works [8], [14]. It has been proven that the PuC technique applied with AT ameliorates attainable Signal-to-Noise Ratio (SNR) even under low-power heat sources [19]–[21]. At present works, ECPuCT can be successfully used in the detection and quantitative evaluation of delamination located in CFRP. The ECPuCT applies a modulated current waveform to excite eddy current, the matched-filter is applied pixel-wise on time trends to retrieve the impulse response of the sample as thermograms [16], [22].

Apart from the improvement of detectability of defects beyond the skin depth based on the ECPuCT method, feature extraction methods are applied in this work, which is critical for the quantitative evaluation of defect. The features are presented by thermal distribution in thermal sequences and transient responses in the time domain. For thermal sequences extraction, the main goal is to define the location of defect based on thermal images. Principal component analysis (PCA) was applied by transforming the raw data into the orthogonal principal component subspace, which also reduces the dimension of data [23]–[25]. Independent component analysis (ICA) was proposed to identify the significant ICs in the mixing observation model. Single-channel blind source separation was proposed in [26], it enables spatial and time patterns to be extracted based on transient thermal response behaviour. Thermal transient response features have been applied to indicate the status of the defect. Fourier transform was used for pulse thermography (PT), it has been proven that the non-uniform heating and surface emissivity variation was removed based on this method [27]. Wavelet transform was proposed which has the potential of automatically selecting both optimal transient frame and spatial scale for defect localization with ECPT system [28].

Thermography signal reconstruction (TSR) and Pulse phase thermography (PPT) are predominantly use in surface defect detection, however PPT needs high peak power heat sources to detect deeper defect. And the combination of TSR and sparse -PCA can be used to identify and classify the limited-depth defect [29], [30]. Since the distribution of the thermal transient response is Gaussian distribution, kernel function was introduced in PCA in previous work. Traditional PCA finds principal linear components to represent the data in the lower dimension. For data with non-linear distribution, PCA is confined in dimensionality reduction. but Kernel-PCA rectifies this limitation by transforming the data into a new low dimensional subspace for linear classification [16], [31]. For the same reason, kernel-ICA was applied in this work for comparison of the performance of those feature extraction methods.

Fig. 1 shows the block diagram of overall work based on the ECPuCT system. In the first stage, the ECPuCT method was first applied to the CFRP sample with manual delamination located at different depths. Then the raw data, presented as thermal sequences, processed with denoising algorithm to remove noise. In the third stage, five different feature extraction algorithms exploited to localize the delamination defect and enhance the delamination area. Based on the experimental results of feature extraction, SNR between defective area and the non-defective area was exploited to compare the performance of those methods. This paper sheds light on the comparison between quantitative defect evaluation equipped with different feature extraction algorithms.

This paper is organized as follows: Section II-A introduces the theoretical background of Pulse-compression theory and feature extraction algorithms proposed. Section III presents details about the ECPuCT experimental setup, and the dedicated CFRP sample. Section IV discusses the results of feature extraction combined with physical meaning, and SNR comparison in the light of their performance. Finally, the conclusion will be made in the end.
II. METHODOLOGY

A. Pulse-Compression Theory

Pulse compression infrared thermography testing is a burgeoning technique that has been used widely in the experimental estimation of impulse response based on the Linear Time-Invariant (LTI) system. In[32], PuC has preponderance in supporting advanced processing algorithms like Thermographic Signal Reconstruction (TSR) and PCA. There is no doubt that PuC is the optimization of Pulse Thermography (PT), it has higher external noise hardiness. In general, the heating stimulus provided by ECPuCT system can be modelled as a Dirac’s Delta function \( \delta(t) \), and the corresponding output \( y(t) \). The temperature response of each pixel in the collected data is consistent with the pulse thermal imaging mode [32]. Features are obtained by analysing the \( h(t) \) within a chosen range of interest \( T_h \) as showed in Fig. 2. In previous works, assuming the pulse heating time is \( T_h \), then the total time interval is \( T + T_h \) [32], [33].

The basic theory of the PuC technique is presented in Fig. 2. Given a coded excitation \( s(t) \) of duration \( T \) and the bandwidth \( B \), and matched filter signal \( \psi(t) \). Their convolution denoted with “∗” approximates the Dirac’s Delta function \( \delta(t) \):

\[
s(t) \ast \psi(t) = \tilde{\delta}(t) \approx \delta(t)
\]

In Eq. (1), an estimate \( \tilde{h}(t) \) of the \( h(t) \) is obtained by convolving the output signal \( y(t) \) with the matched filter \( \psi(t) \).

Arbitrary White Gaussian Noise (AWGN) assumed as \( e(t) \), which is uncorrelated with \( \psi(t) \). Then the output \( y(t) \) acquired from: \( y(t) = h(t) \ast s(t) + e(t) \). The impulse response \( h(t) \) can be estimated by the assumed code excitation \( s(t) \) and then by convolving the output \( y(t) \) with matched filter \( \psi(t) \) [34]:

\[
\text{tildeh}(t) = y(t) \ast \psi(t) = h(t) \ast s(t) \ast \psi(t) + e(t) \ast \psi(t)
\]

\[
\approx h(t) \ast \tilde{\delta}(t) + \tilde{e}(t) \approx h(t) + \tilde{e}(t)
\]

In Eq. (2), \( s(t) \ast \psi(t) \) equals to the \( \tilde{\delta}(t) \). By this assumption, \( \tilde{e}(t) \) has theoretically lower energy than \( e(t) \) due to the irrelevancies between \( \psi(t) \) and \( e(t) \). Based on the model, PuC can provide power for the system over an extended period, and an approach estimation achieved at the end [32]. Due to the energy enhanced, the SNR increase in theory. In paper [16], the SNR gain can be enhanced by extending the time duration \( T \) or bandwidth \( B \). To optimize \( \delta(t) \) and gain higher SNR, literature addressed that the optimal choice of matched filter is \( \psi(t) = s(−t) \), in term of quality of the reconstruction, the Wiener filter can be applied to enhance the quality [32], [35]. In this paper, \( s(t) \) is a Barker Code (BC) of order equal to 13 and the matched filter \( \psi(t) \) has been chosen simply to be the time-reversed sequence of the input coded signal \( s(t) \).

B. Image PCA and Impulse Response PCA

The temperature distribution of the sample surface varying with the time recorded by an IR camera, which is a 3-D thermal image sequence along with time. It is very inefficient to analyze temperature distribution images contains mass information. Therefore, it is of considerable significance to extract the information from image sequence in time domain effectively by using a feature extraction algorithm.

Principal component analysis (PCA) aims for the optimal set of vector bases to represent the relationship between data. The impulse response of each frame in the thermal sequences regarded as an independent variable in image PCA. Each extracted Principal component (PC) is a linear combination of the original frame. PCs constitute the basis of vector space respectively and arranged in order of diminishing variance. It also means PC with large variance is most likely to contain significant thermal information.

Fig. 3 presents the process of image PCA. Firstly, to facilitate the use of PCA, the original 3-D data converted to a 2-D data. Then each column vector of this 2-D matrix represents the temperature curve of different single-pixel varying with time. For image PCA, the black row represents the thermal response distribution of a frame at a time duration, PCA reduces the dimensionality of data on the time axis \( N_t \). Compared to the image PCA, impulse response PCA regards the impulse response of each pixel rather than each frame in the thermal sequences. It is worth noting that each PC extracted from raw data represents a linear combination of the original impulse response. Fig. 3 displays the diagram of impulse response PCA at the bottom, a column of pixels represents the impulse response of single-pixel varying with frames (\( N_t \)).

In accordance with the theory of ECPT, the interaction of eddy current distribution gradually decreases as the depth of defect increases. In the heating stage, the distributions of eddy current are independent as each other, which form independent Joule heat source. Then the heat inside material is diffused along with fiber orientations. The heat of each region interacts only with its neighbours. It is generally assumed that the heat distribution on the surface determined by the characteristic of electricity, magnetism, heat, etc. In this case, the heat distributions of two distant regions are independent of each other.

Compared with PCA, Kernel-PCA can project undivided linear data to higher dimensional space for dimensionality reduction. Assuming the output matrix \( Y(t) \) observed by the IR camera comprise of single-pixel’s impulse response matrix
can be projected as vectors \( \alpha \) obtained eigenvectors with the largest eigenvalues are selected for projection in this region as far as possible. Thermal response signal separation extraction for separation of heat distribution from different independent of each other, ICA can be applied in feature theses principal components are hard to profile. On account thermal response, aliasing of thermal response from different the thermal video as an independent variable. Compared to the traditional PCA, this method processes the impulse response of each pixel rather than each image in the paper. Compared to the traditional PCA, this method processes

In Fig. 3, Diagram of image PCA (upper) and impulse response PCA (bottom).

\[ X(t), Y(t) \text{ expressed as follows:} \]

\[ Y(t) = [X_1(t), X_2(t), X_3(t), \cdots, X_{N_x \times N_y}(t)] \]  

\[ (3) \]

To introduce the kernel function, the input matrix is projected to the kernel space \( \Phi \), the kernel matrix \( K(i,j) \) obtained as follows:

\[ \frac{1}{N_x \cdot N_y} \sum_{i=1}^{N_x \times N_y} (\Phi(X(t)) - \frac{1}{N_x \cdot N_y} \sum_{j=1}^{N_x \times N_y} \Phi(X(t))) = \frac{1}{N_x \cdot N_y} \sum_{i=1}^{N_x \times N_y} (\Phi(X(t)) - \frac{1}{N_x \cdot N_y} \sum_{j=1}^{N_x \times N_y} \Phi(X(t))^T) \]

\[ (4) \]

In Eq.4, the Gaussian kernel function defined as:

\[ \Phi(X(t)) = \exp \left( -\frac{\|\phi(X(t)) \cdot \phi(X(t))^T\|^2}{2\sigma^2} \right) \]

\[ (5) \]

The kernel matrix \( K(i,j) \) named as \( K \) for simple, the eigenvectors \( \alpha \) of kernel matrix can be obtained as:

\[ \lambda_i \alpha_i = K \alpha_i \]

\[ (6) \]

In Eq.6, \( \lambda_i \) is the corresponded eigenvalue. Based on the obtained eigenvectors \( \alpha_i \), then the enhanced thermal pattern can be projected as:

\[ X_d(t) = [\alpha_1, \alpha_2, \cdots, \alpha_T] Y(t)^T \]

\[ (7) \]

K-PCA maps the impulse response of single-pixel varying with frames \( N_f \) into Gaussian space, the ten eigenvectors with the largest eigenvalues are selected for projection in this paper. Compared to the traditional PCA, this method processes the impulse response of each pixel rather than each image in the thermal video as an independent variable.

Although PCA focus on principal components contain the thermal response, aliasing of thermal response from different regions blurred the physical meaning of the PCs. Therefore, theses principal components are hard to profile. On account of the thermal responses from different regions that are the independent of each other, ICA can be applied in feature extraction for separation of heat distribution from different regions as far as possible. Thermal response signal separation based on independent component is a process of constantly searching for the best linear transformation [32], [33]. In this paper, the implementation of ICA based on Maximum likelihood estimation and Fast ICA. The mathematical model and calculation method are introduced in [36].

C. Feature Extraction Comparison

In this study, SNR value comparison is used to evaluate the performance of feature extraction algorithms from data [35]. This method is suitable to compare the performance of extraction algorithms in dealing with different depth defects. The value of SNR reflects the contrast between the defective area and the non-defective area, which proves which algorithms are outstanding. Considering that different pixel responses are interfered with by noise in difference, manual selection of 2 \times 3 pixels region contrasted with the sounding area. The calculation operated by the following formula:

\[ \text{SNR}(t) = \frac{h_D(t) - \bar{h}_D(t)}{\sigma_h(t)} \]

\[ (8) \]

In Eq.8, \( h_D(t) \) is the impulse response of defected area averaged over a manual selection region, \( \bar{h}_D(t) \) is the impulse response averaged over whole thermal image and \( \sigma_h(t) \) is the standard deviation of the manual selection region same as \( h_D(t) \).

III. EXPERIMENT SETUP

A. Eddy Current Pulse Compression Thermography Setup

The system of ECPuCT that showed in II-C mainly composed of a signal generator, induction heating device, excitation coil, IR camera, cooling device and PC. The signal generator sends excitation signal to the induction coil, and a trigger signal sent to the IR camera to record thermograms at 50FPS at the same time. The induction heating unit is Cheltenham EasyHeat 224, which has a maximum excitation power and current value of 2.40 kW and 400 A, respectively, and a tuneable carrier in the 150-400 kHz range. The water-cooling device is used to cool the excited coil while the coil
is held 3.00mm from the sample surface to ensure that the heating of the sample is volumetric heating.

The excitation coil uses a high conductivity copper hollow control with a diameter of 6.35mm as a rectangular coil. The thermal imaging camera uses FLIR’s SC7500, the thermal imager has an InSB infrared detector with a sensitive wavelength of 3-5 μm, a measurement accuracy of ±1°C, a noise equivalent temperature difference of less than 20mK, and a resolution of 2.

B. Dedicated Sample of CFRP

Fig. 5 shows the structure of CFRP, the dedicated sample contains twelve piles of carbon fiber fabric, the areal density is 0.2 g/m² and the fiber orientation are 0° or 90°. The lateral length is 200mm, and the width is 240mm, the total thickness of the sample is 2.80mm. The artificial delamination defects realized by inserting square pieces of Teflon tape with lateral dimensions of 20mm × 20mm. Nine artificial defects were inserted at increasing depth. The shallowest defect is #1 and is placed under 2nd layer at a depth 0.46mm from the surface, the most buried defect is #9, and is placed under the 10th layer at the depth 2.30mm.

IV. RESULTS AND DISCUSSION

A. Image PCA

As explained in section II-A, the image PCA algorithm is applied to extract the delamination feature and enhance the patterns. Fig. 6 shows the extracted thermal patterns from original thermal sequences. The heat produced from eddy current transfers along the direction of carbon fibers. The temperature distribution of carbon fiber structure in the defective area is abnormal, and the temperature is higher than that of the carbon fiber structure in the defective region. Delamination will affect the distribution of the transverse eddy current field. If the eddy current cannot flow directly through the layered position, it will bypass, which makes the delamination unable to obtain the eddy heat.

In this work, the impulse response is a sequence of 1500 frames corresponding to the stimulant duration. About 300 frames range from the 650th frame to the 949th frame as the feature extraction data, which covers the heating and cooling stage and ensures the validity of the data to the greatest extent.

The 1st pattern is the heating pattern that contains most information of frames, it also contains a fuzzy effect caused by transverse heat transfer, so the distribution of temperature information is vague. The 2nd pattern explicitly shows the regular distribution of carbon fibre texture in the defective area without mild fuzzy effect, which forms a sharp contrast to the carbon fibre structure. In this pattern, the location of delamination can be roughly estimated. The 3rd pattern shows the apparent shape of delamination as expected because it contains the essential defect information. Since the electric and thermal conductivity transfers along the fiber orientation based on sample structure, which makes the edges of delamination hotter than region of delamination. However, it has a lower contrast between sounding area and defective area, which leads to the vague when the depth of defect becomes deeper such as #defect3 PC2.

For image PCA, the followed patterns contains less useful information, so it is generally not included in the scope of analysis. Besides, for more profound defect, the quality of patterns become obscure, which is the reason for the introduction of impulse response PCA.

B. Impulse Response PCA and Kernel PCA

Impulse response PCA has the advantage of feature extraction for the thermal response of each pixel, these patterns displayed in Fig. 7. In general, the first three patterns satisfy the description of image PCA. There is the same problem as image PCA of PC1s, fuzzy effect leads to the image blurring so that enough defect information cannot be obtained.
The 2nd pattern shows the delamination in lower contrast while the 3rd pattern shows it in higher contrast, the reason is their corresponding eigenvectors are supposed to be orthogonal with each other. It is worth notice that 3rd PCs of impulse response PCA presented reversed contrast, the orthogonality of 3rd PCs between impulse response PCA and image PCA has been proven in Fig. 8. The location and shape of delamination are more easily identified by image operation.

When dealing with deeper defects such as defect#9, the performance of traditional PCA is not ideal. Kernel PCA was introduced to enhance thermal patterns in this work. According to section II, Kernel-PCA considers the impulse response of a single pixel as an independent variable, which makes the PC extracted is a linear combination of impulse responses that form the vector space respectively and arranged in order of variance reduction. In Fig. 9, the contrast between defective area and sounding area presented more remarkable with Kernel PCA. For deepest defect #9, Kernel PCA exhibits more interference immunity than PCA even in 4th PC with low-contribution eigenvalue. However, it is obvious that some K-PCA patterns present opposite contrast, the reason is the kernel-PCA cannot arrange order of eigenvectors before projection, thus the patterns arranged as random. K-PCA makes the contrast large enough to determine the delamination location but keep more thermal information result in the coverage the edge information of defect. The enhanced patterns emphasize the defect with a larger contrast between defective area and non-defective area, which also provides the proper regions of impulse response for evaluation.

C. ICA and Kernel ICA

ICA was applied in this work to extract the features and separate the thermal distribution from different regions. Due to ICA considers the separation of thermal distribution of impulse responses, thermal responses along the fiber orientations preserved in patterns, which displayed in Fig. 10. In addition, the edge information is not covered by thermal information while keep the higher contrast between defective area and non-defective area. In the first patterns reconstructed by the first independent components, non-uniform heating along the coil can be eliminated. Based on the patterns of defect#1 and defect#5, the contrast between regions is obviously higher than that of PCA methods. Therefore, the ICA based on image construction method can be used to reduce the effect of non-uniform heating, enhance the delamination detectability, and separate the thermal responses.

The preponderance of the ICA algorithm embodies in dealing with deep defect such as defect#9, the results of defect#9 showed in Fig. 10. Those patterns based on ICA present clearly texture of carbon fibre and location of the delamination with slightly edge. Compare to K-PCA, ICA with limited improvement enhances patterns by separating the thermal information from defective area and non-defective area, but the computational time was greater than PCA (ICA: 15.98s, PCA:9.7296s) when dealing with sample, and thus the need of ICA is considerable. To further compare their performance, Kernel-ICA was introduced in this work.
In Fig. 11, combining with mesh figure of defect#1 based on PCA and K-PCA, ICA with kernel function is significantly to improve the contrast between defective and non-defective regions than K-PCA and PCA. There is a noticeable detail of K-ICA pattern, the transverse heat propagation along with fibre direction affect the thermal distribution heavily. Although the texture of carbon fibre showed clearly than other methods, the edges of delamination are not presented clearly as K-PCA in the pattern.

This section discussed the results of the feature extraction. In terms of pattern quality, the quality of K-PCA presents more of the edges of delamination, and the results of ICA show more contrast between the defective area and the non-defective area. Both of PCA and ICA, they do not need to make a specific assumption of the source signal, the PCA considers that the most of useful information for a random signal included in the variance, the ICA aims at the separation of independent components composed thermal information and defect information. Therefore, their results highlight different details. In order to compare the advantages and disadvantages of these methods, the next section presents the comparison of SNR value to evaluate their performance.

D. Features Comparison

In Fig. 12, the SNR of image PCA is linear and monotonic decline, which is accorded with the theory of image PCA. Despite some errors and noise effects, the SNR of the defects corresponding to the six principal components decreases with the increase of depth. Because impulse response PCA showed focus on the instantaneous thermal response of a single pixel, the data are distributed nonlinearly. The decline rate of impulse response PCA is obviously slower than that of image PCA when dealing with deep defects. Therefore, impulse response PCA is more reliable than image PCA method.

The SNR of K-PCA declines rapidly between defect#1 and defec#2, which indicates that the heating information contained in the principal component is reduced heavily. After the second point, the decrease of information corresponding to the principal component becomes gentle, most of SNRs are concentrated in the range from 0 to 0.1. The results also prove that when the data mapped into Gauss space, the data become separable linearly. Therefore, most of the heating information that affect detection is filtered out. Combining with the results of K-PCA, K-PCA performs better than traditional PCA in detecting delamination of CFRP in practice.

Due to the skin-effect, the eddy current density decayed exponentially, which reflected in the figure. There is a slight difference between ICA curve and K-PCA curve, which indicates that ICA does not improve image quality. According to the ICA theory, ICA capable of the separation of independent components and screen out the most differential components for image reconstruction. Therefore, the patterns of ICA reflect the differences between individual thermal responses, but SNR values not improved.

V. Conclusion

In this work, feature extraction techniques of impulse response have been exploited in terms of principal component analysis (PCA), kernel principal component analysis (K-PCA) and independent component analysis (ICA). The conclusion is as follows:

Traditional PCA has the advantage of simple implementation and fast calculation speed. However, the limitations of PCA are obvious, such as it can solve the linear correlation well, but there is no way for high-order correlation.

For data possess high-order correlation, kernel PCA is worth considering because the non-linear correlation is converted to linear correlation by kernel function. Since the thermal response distribution is consistent with a Gaussian distribution, Kernel-PCA with Gaussian kernel adopted in this work. However, K-PCA and PCA affected by non-uniform heating pattern.

Because of the independence and non-correlation between thermal responses, ICA was applied in feature extraction. Compared with PCA methods, ICA performs better when dealing with deep defect.

According to the properties of SNR curve, the performance of K-PCA is the most stable and corresponds to the corresponding physical phenomena. Eddy current density exponential decays with the depth increases, which corresponds to the SNR curve of K-PCA is exponential.

Based on the drawbacks discussed before, the future work will investigate extracting multiple defect features and evaluating their performance through feature selection and fusion.

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