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A Sliding-Window Principal Component Thermography Reconstruction Approach for Enhancement and Identification of Electronic Components Internal Structure

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Highlights

- A novel thermography inspection post-processing scheme for electronic components.
- A breakthrough in internal structure thermography inspection for highly-integrated and encapsulated components.
- A investigation of sliding window embedded scheme for detection contrast enhancement in thermography.
- A structural identification and screening tool for the unverified electronic components cost-effectively.

Abstract

Electronic supply chain vulnerability has been threatened by counterfeits for decades and as a result, the authentication and quality of Electronic Components (ECs) are highly valued by stakeholders for safety-critical industrial systems. Thermography Nondestructive Testing (NDT), offering a rapid inspection while covering a large area within a short time frame, is a promising technique to inspect the integrity of ECs. However, recognising the internal structural layout directly through a packaged EC from thermography images is still a challenge due to its sealed and cramped structure. In this research, we propose a Pulsed Thermography (PT) based data analysis method for enhancement and identification of the layout of die and lead frame in ECs. The proposed solution combines the Sliding Window (SW) concept, Thermographic Signal Reconstruction (TSR) and Principal Component Thermographic (PCT) technique, named SWPCT, to enhance the contrast of die, die substrate and lead frame. Compared to the conventional full-scale PT image analysis, the proposed method presents its superior sensitivity in small thermal features by reducing the spatial thermal information redundancy benefiting from the sliding window PCT analysis. It overcomes the structural thermograms obstruction from the thick packaging, reveals the hidden die and lead frame layout and suppresses the noise simultaneously. By selecting a proper window size, this paper reveals that SWPCT can reconstruct the position and dimension of die and die substrate in ECs, and spatially distinguish the lead frame layout. Two groups of typical OpAmps chip samples with internal structure diversity (X-ray observed) were tested using PT to demonstrate the effectiveness of the proposed method. Simulation data were also used to verify this approach. This research could unlock the challenge of thermography-based inspection for key internal structure in the encapsulated integrated components.

Keywords: Electronic Component; Thermography Inspection; Sliding Window Analysis; Principal Component Thermography;

1. Introduction

Electronic components (ECs) are widely used in critical systems in manufacturing, transport, aviation, power generation, and cybersecurity. An unexpected failure caused by counterfeiting ECs can lead to unstable and unreliable operational performance, cause unpredictable system malfunctioning or failure, operators' injuries or catastrophic economic loss [1, 2]. Detecting various types of counterfeit is a challenging process occurring in every step of the global supply chain, persecuting stakeholders to invest budget for improving the non-destructive verification technology [3, 4].

The external inspection of packaging texture, material corrosion, lead pins damage and surface marking has been used in the supply chain [5-7]. But it has a fundamental drawback of the incapability in dealing with those ECs with internal structural anomalies. This issue has been captured by illegitimate manufacturers and grey market dealers who are trying to slip through this loophole with the development of counterfeiting methods [8]. X-ray imaging [9] and TeraHertz (THz) testing [10, 11] are capable to analyse the accurate internal physical properties such as wires, circuit joint and package material, but cannot be widely used due to either being destructive with low throughput and a high capital cost per inspection unit, or overly sophisticated for unskilled operators [12, 13]. Therefore, an intuitive, non-contact, high-efficient and low-cost non-destructive inspection technique is highly demanded to deploy the first stage large scale inspection efficiently for reducing the proliferation of ECs with internal structural anomalies.

Thermography is a well-established non-destructive testing (NDT) approach based on the study of the evolution of temperature distribution on the surface of the sample of interest. As a highly efficient and powerful NDT technique, pulsed thermography (PT) offers a rapid, contact-free, high-efficient inspection and shows promising applicability to *in-situ* monitoring applications [14, 15]. Beyond defect detection, quantitative characterisation of internal structural information including shape, size and depth, and estimation of thermal properties have been proven to be essential and decisive for through-life engineering [16-18]. The features within the transient temperature of the inspected object have been widely used to evaluate material or structural discontinuity within the object. However, related research focusing on the internal spatial reconstruction in EC using thermography is still limited.

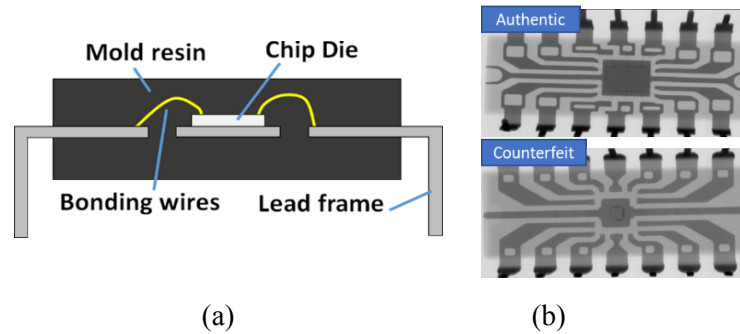


Figure 1. Illustration of a typical EC and authentic and counterfeit chips (a) The simplified structure of a typical dual in-line package EC; (b) Internal variation between authentic and counterfeit in X-ray images.

Figure 1(a) presents a typical internal structure of dual in-line package EC which generally has a dimension within 10 mm. Die and lead frame are the most common places incurred structural anomalies in counterfeits [19, 20], as demonstrated in Figure 1(b). Due to the complex lateral structure of die, mould and lead frame been stacked into a narrow space inside the ECs, the structure reconstruction using PT thermal signal challenges the conventional analysis technique. Several studies have proposed methods to identify the counterfeit sample from thermal time-domain signals using PT inspection [21, 22]. However, they can not clarify exactly what the internal structure difference is. The thermal inertia effect of external thick mould material packaging will heavily undermine the Signal Noise Ratio (SNR) in the space domain for structure feature. Additionally, the spatial noise caused by surface uncertainty of the EC sample will intensify the difficulty of the reconstruction aim [23]. When all these surface and subsurface effects are combined with the surroundings affecting the thermograms, straightforward interpretation of internal structure turns out to be challenging. Thus, to enhance the anomalies detection for ECs using PT, advanced post-processing methods are required for structure reconstruction analysis.

The Thermographic Signal Reconstruction (TSR) [24] method is remarkable at improving the temporal resolution and reducing time-domain noise of the thermogram sequence and consequently promoting the time-domain sensitive features. By focusing on thermal sequence reconstruction and alleviating the transient noise simultaneously, TSR-based thermogram analysis has been applied to characterise defect and transform the thermography data into RGB images. Another promising method is Principal Component Thermography (PCT) [25, 26] that uses Principal Component Analysis (PCA) in a 3D thermographic image sequence. The time-domain feature from PCA has been used for counterfeit identification in ECs [22, 27, 28]. PCT is a statistical tool used for identification of specific image patterns in thermograms, depicting similarities and differences of specific patterns by decomposing data to singular modes. The PCT images have been demonstrated to be powerful at extracting spatial features of defects in thermography data. Traditional PCT in full image scale is capable of detecting a variety of defects in a relatively uniform structure, such as flat-bottom holes, delamination and corrosion. However, it is incompetent for the distribution identification of a complex structure component, especially for the ECs with lead frame and mould materials integrated into a few millimetres area.

This paper reports a novel method of internal structure layout enhancement and identification of ECs based on the PT inspection, especially for highly integrated components. By developing a sliding-window PCT, this method reduces the surrounding redundancy influence and improves the spatial feature extraction. The proposed methodology is presented in Section 2. The experimental results are presented in Section 3. Results discussion are given in Section 4, while the conclusions are given in Section 5.

2. Methodology

In this study, we propose a new internal structure reconstruction technique for ECs with validation using numerical modelling. By developing a structural feature extraction strategy, the difference in the internal structure of die and lead frame from different manufacturers can then be identified and quantified. Figure 2 presents the flowchart of the proposed methodology for EC inspection.

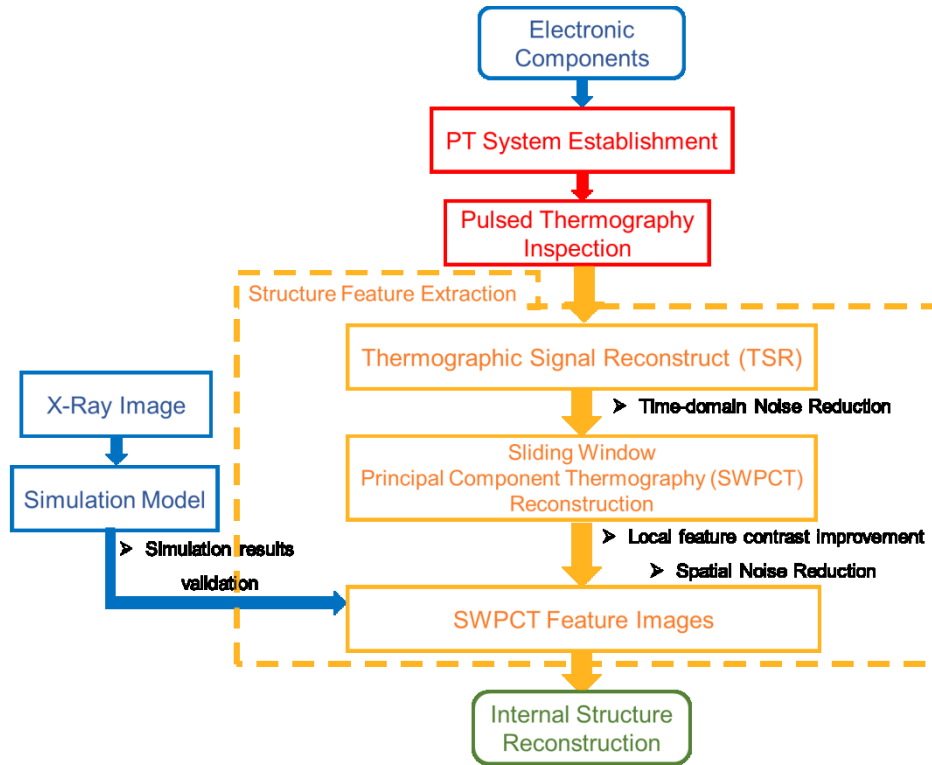


Figure 2 The flowchart of the proposal methodology

An experimental system is established to implement the PT inspection of two groups of EC samples with two types of internal structure variation. To reconstruct the internal structure of ECs, we propose a Sliding Window Principal Component Thermography (SWPCT) reconstruction algorithm coupling with Thermographic Signal Reconstruction (TSR) to extract the spatial distribution of the die and lead frame. In this paper, the 1st and 2nd derivatives of TSR data, which are more sensitive to the variation of inner structure than the raw signals, are used for further analysis. SWPCT focuses on spatial feature extraction and enhances the local feature contrast of the internal die and lead frame, which are hidden in the derivative data. It pixel-wisely reduce the time-spatial thermal influence by local PCT and smoothly reconstructs the relevant feature by a sliding window. It also suppresses the spatial noise using a window with an appropriate size. The obtained feature image from SWPCT presents the distribution of die, die substrate, and lead frame. By quantitative calibration of the die and visualisation of the lead frame, the internal structures of different ECs are properly reconstructed. To validate the proposed method, a finite element modelling (FEM) simulation for different internal structural variation (informed by the X-ray images) is built to predict the thermal behaviour of ECs in PT. The simulation data is then used to verify the proposed method.

2.1 Electronic Components

To achieve the proposed technique, this research starts with a common type of electronic chip: Operational Amplifiers (OpAmps). A total of 8 OpAmps were collected from two trade markets to investigate their thermal responses in PT. All samples are common dual in-line package chips and are designed for the same electronic purpose. They have an almost identical external appearance except for surface markings. It should be noted that this study has no interest to investigate surface labelling. To reveal the internal structure of these chips, an X-ray inspection was adopted to obtain their lead frame and die details. Figure 4 presents the exterior dimensions, surface markings, and X-Ray images of the 8 samples, which are categorised into two groups according to the surface markings.

As shown in surface marking, the chips of Group A (from '01' to '04') are from the same origin marked by "CHN" and those of Group B (from '05' to '08') are original from "MAL". The markings of "UA741CN" suggests the same electronic function. The ECs of Group B were tested by the electronic function testing and proven to be malfunctioning, while the ECs in Group A were verified as sound ones. The internal structure of the lead frame and die within each group is consistent, respectively. Two main types of internal structural variations, including die size and lead frame layout, can be observed between the two groups in the X-ray images. Firstly, the chips in Group A exhibit a left layout in lead and die position while those of Group B exhibit the right layout. Secondly, Group B components have a bigger die size than those in Group A. Based on these preliminary information set, the strategies from both simulation modelling and experimental inspection are discussed below.

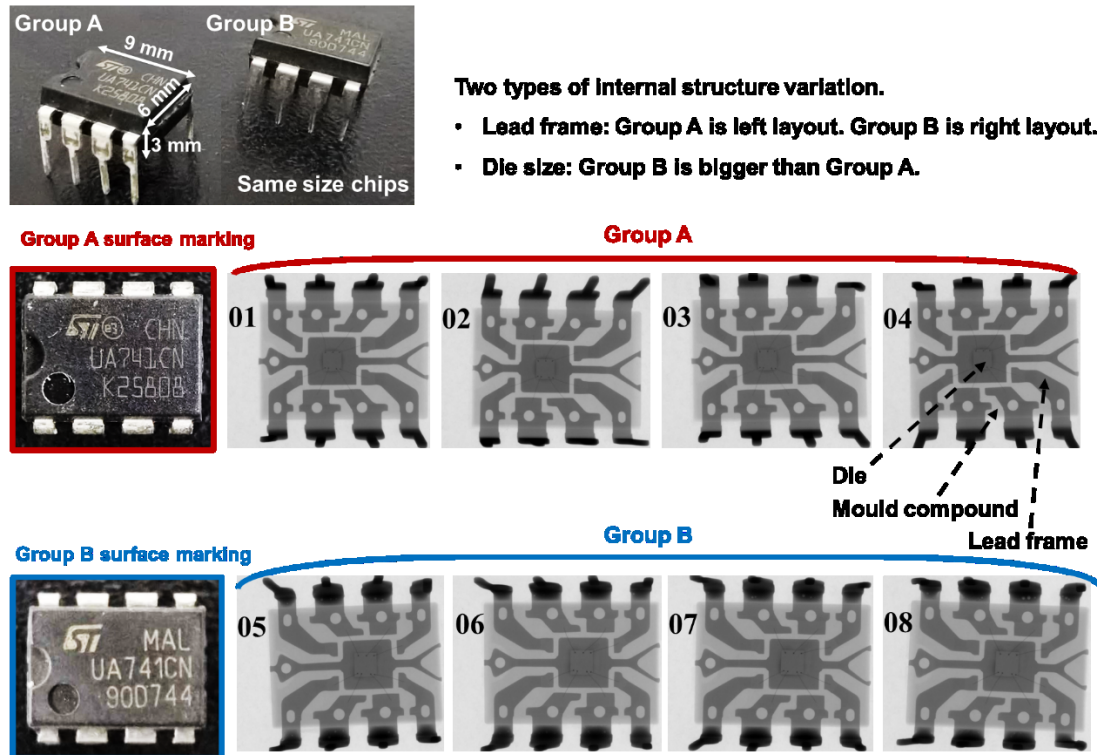


Figure 3 The digital images and X-ray images of two groups of chips, where the differences in surface and inner structure are presented.

2.2 Experimental system

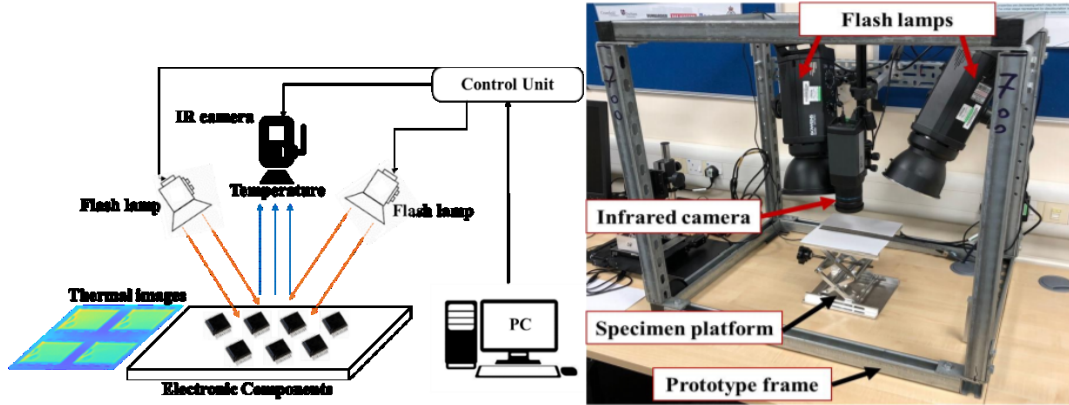


Figure 4 PT inspection for ECs; (a) Principal of PT. (b) Experimental system

Figure 4 illustrates the employed pulsed thermography system, where a short and high-energy light pulse was projected onto the sample surface through two commercial flash lamps. The temperature measuring device was a FLIR A615 series IR camera with a long-wave (7–14 μm) uncooled focal plane array. The top surface temperature of ECs was captured with a maximum 640×512 pixels resolution and a framerate of 25 Hz. Both the camera and the lamps were synchronised and controlled by a PC to perform an automated inspection. A close-up IR lens with a magnification factor of $\times 2.9$ was adopted to achieve a 50 μm spatial resolution and a field of view of 32×24 mm. The maximum energy applied in the inspection was approximately 1.4 kJ over an area of 500 mm in diameter. The samples were placed with their surfaces perpendicular to the IR camera's line of sight at 85 mm from the lens. To reduce the uncertainty of heat uniformity, the samples were placed at the centre of the camera view. Both lamps heated the samples with a 10 ms pulse duration and maximal energy.

In the experiment, the two groups of ECs were inspected one by one. Each thermal image sequence was captured with a duration of 8 second, where 200 frames were captured for analysis. To exclude the influence of external pins and boundary, a region of interest (ROI) for each sample was selected covering 90% area around the centre of the chip. Between each inspection, a five-minute interval was implemented to ensure the lamps and camera have reached equilibrium temperature.

2.3 The proposed reconstruction method

a) Thermographic Signal Reconstruction (TSR)

The relation between the surface temperature of each pixel and the input energy can be expressed as Eq. (1) [24]:

$$\ln(\Delta T(t)) = \ln(T(t) - T_0) = \ln\left(\frac{Q}{e}\right) - \frac{1}{2}\ln(\pi t) \quad (1)$$

where $T(t)$ is the surface temperature at time t ; T_0 is the initial temperature; Q represents the input energy per unit area; $e = \sqrt{k\rho c}$ (the square root of the product of thermal conductivity

k , density ρ and heat capacity c) is the thermal effusivity of the tested sample. In practice, it is rational to approximate the logarithmic curve of temperature-time during decay by a polynomial fitting on each pixel as given in Eq. (2), where N and a_i are the TSR order and coefficients to be estimated.

$$\ln(\Delta T) = a_0 + a_1 \ln(t) + a_2 [\ln(t)]^2 + a_3 [\ln(t)]^3 + \dots + a_N [\ln(t)]^N \quad (2)$$

The 1st and 2nd logarithmic derivative signal derived from Eq. (2) can be calculated using Eq. (3) and (4)

$$\frac{d \ln(\Delta T(t))}{d \ln(t)} = \sum_{n=0}^N a_n \cdot n \cdot (\ln(t))^{n-1} \quad (3)$$

$$\frac{d^2 \ln(\Delta T(t))}{d^2 \ln(t)} = \sum_{n=0}^N a_n \cdot n \cdot (n-1) \cdot (\ln(t))^{n-2} \quad (4)$$

b) Principal Component Thermography (PCT) using Singular Value Decomposition (SVD)

On the receipt of 1st and 2nd derivative TSR signals, the Principal Component Thermography (PCT) is employed to analyse the spatial thermal features. The key idea of PCT is to transform the time-based information to a domain where the spatial temperature variation detected from the thermograms can be associated with the structure discontinuity in samples. PCT is derived from the Empirical Orthogonal Functions (EOFs) in PCA to extract the spatial features and reduce undesirable noise by projecting original data onto an orthogonal components system. In this research, the SVD-based PCA is used to calculate PCT to reduce the computation burden from the transient thermal image sequence.

Before conducting SVD, the thermal raw 3D data matrix $A(x,y)$ is normalised using Eq. (5)

$$\hat{A}(x,y) = \frac{A(x,y) - \mu_{x \text{ col}}}{\sigma_{x \text{ col}}} \quad (5)$$

where $\mu_{x \text{ col}}$, $\sigma_{x \text{ col}}$ denotes the mean and covariance of each frame, and can be calculated using Eq. (6) and (7), respectively.

$$\mu_{x \text{ col}} = \frac{1}{p \times q} \sum_{n=1}^{p \times q} A(x,y) \quad (6)$$

$$\sigma_{x \text{ col}}^2 = \frac{1}{p \times q - 1} \sum_{n=1}^{p \times q} (A(x,y) - \mu_{x \text{ col}})^2 \quad (7)$$

Subsequently, matrix $\hat{A}$ can be decomposed by:

$$\hat{A} = U \Sigma V^T \quad (8)$$

In Eq. (8), U is the orthonal matrix and its columns comprise the orthogonal statistical modes as EOFs which describe the spatial variation in the thermograms. V^T is a $M \times M$ dimensional matrix and its rows comprise the Principal Components (PC) which describe the time-domain variation. Σ is a diagonal matrix containing the eigenvalues (ranked in

descending order) corresponding to PC eigenvectors in the matrix V^T . Then the PCT image is obtained by reranking the vector EOF into the 2D image format [25].

However, for the scenario of complex integrated structure distributing within a small size of ECs (within 10 mm), the distance between the die and each lead is highly limited. Besides, the relatively large thickness of the upper mould material leads to a spatial thermal blurring which hides the internal structural feature even in the derivative images. After SVD, the EOFs representing a spatial variation of full image scale contains too much non-structure corresponding correlation and cannot extract the local structure diversity, and includes the influence of full image noises. Consequently, too much spatial redundancy will undermine the PCT enhancement and identification of die and lead frame. Therefore, the PCT in the full image scale is not capable of discriminating the detailed internal structure variation of EC.

c) Sliding Window PCT (SWPCT) Reconstruction

We propose a sliding window method to solve the above problem. Figure 5 describes the flowchart of the proposed SWPCT. Instead of directly calculating the full image scale SVD for PCT, SWPCT initially employs a 2D spatial window to extract the windowed 3D data cube, which is then processed with the SVD-based analysis to acquire the windowed PCs and EOFs data. By only preserving the windowed SVD 1st order data and reconstructing using inverse SVD, the most principal thermal variation of spatial and transient information within the windowed local region are dedicatedly enhanced. Theoretically, it should be sensitive to the die and overlapped die substrate which is the biggest internal concentrated part by referencing the structure of ECs. Furtherly, the spatial mean value of reconstructed data is calculated and set at the selected window centre pixel. The results produced by this method will not only enhance the local feature contrast but also eliminate the local spatial noise. Finally, by sliding the window pixel-wisely, an SWPCT image in the full image scale can be obtained. We consider the case where $[M, M]$ window is shifted on the area of (x_0, y_0) th pixel as the centre, and denote $\hat{A}_{x_0, y_0}(M \times M, t)$ as the SVD normalised and windowed image sequence data for PCT analysis. Eq. (9) shows the SVD analysis within the selected window and Eq. (10) presents the calculation of SWPCT reconstructed data for each sliding window using the proposed method.

$$\hat{A}_{x_0, y_0}(M \times M, t) = U'_{x_0, y_0} \Sigma'_{x_0, y_0} V'^T_{x_0, y_0} \quad (9)$$

$$\begin{aligned} & \hat{R}([x_0 - \frac{M}{2} + 1, x_0 + \frac{M}{2}], [y_0 - \frac{M}{2} + 1, y_0 + \frac{M}{2}], t) \\ &= \text{InverseSVD}_{\text{reranking}}\left(\frac{\sum_{k=1}^K u'_{kx_0, y_0} \sigma'_{kx_0, y_0} v'^T_{kx_0, y_0}}{K}\right) \end{aligned} \quad (10)$$

where U'_{x_0, y_0} , Σ'_{x_0, y_0} and $V'^T_{x_0, y_0}$ denotes the EOFs, eigenvalue, PCs matrix after SVD

within the $[M, M]$ window, respectively. The $\hat{R}$ denotes the SWPCT reconstructed results using the inverse SVD and re-ranking to the 3D image sequence data. The symbols of u' , σ' , and v' denote the EOFs, eigenvalue, PCs of first K order selected, respectively.

One of the advantages of SWPCT is that it focuses on the local spatial variation hidden in the full image scale. By eliminating the data correlation through PCT and extracting internal structural relevant features, it enhances the features by focusing on the windowed area and ignores the disturbance of surroundings. It effectively enhances the contrast of thermal features that represent the internal structure components (die or lead frame). Another advantage is that it eliminates the high-frequency spatial noise. Combining TSR, PCT with a sliding window, the proposed method returns a smooth image with low noise but without losing important features.

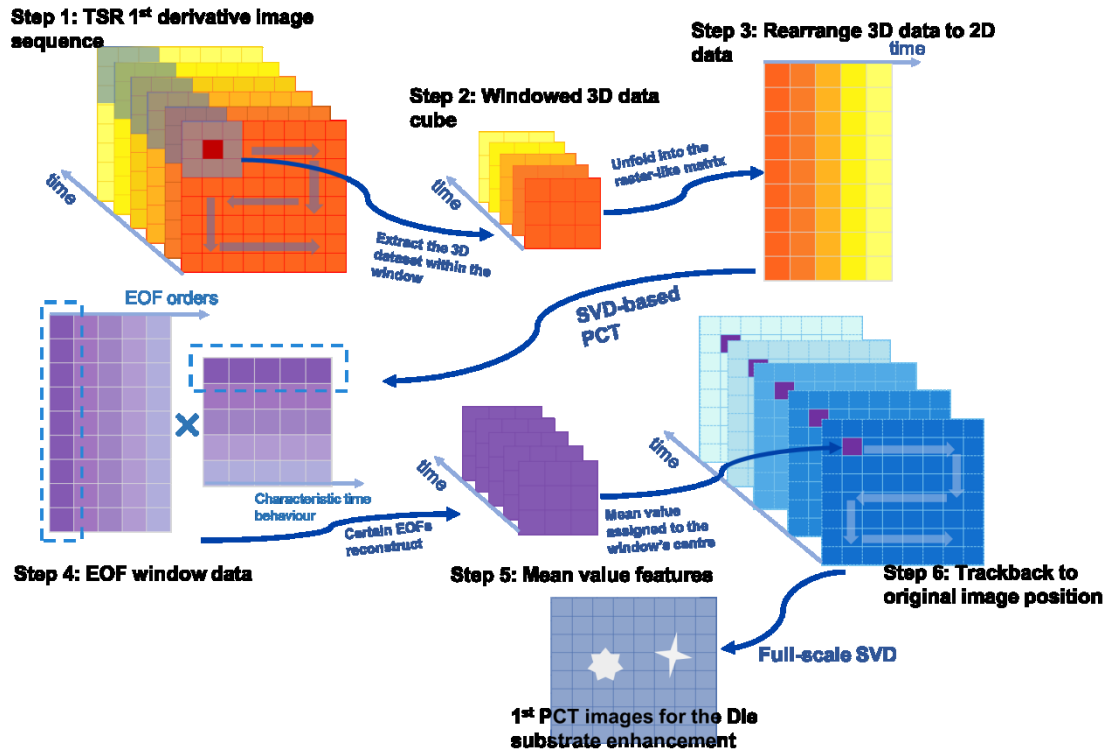


Figure 5 The SWPCT for internal structural feature enhancement.

3. Results

3.1 Die enhancement of the experimental data

Figure 6 presents the raw thermal images using the developed testing prototype. The image set shows the first thermal frame after the flash (at 0.04 s for this study) of all 8 chips. It should be noted that they were captured one by one, where the location in the scene and other experimental parameters are identical. This figure presents no obvious pattern in the raw Infrared (IR) images that can reliably distinguish these two groups.

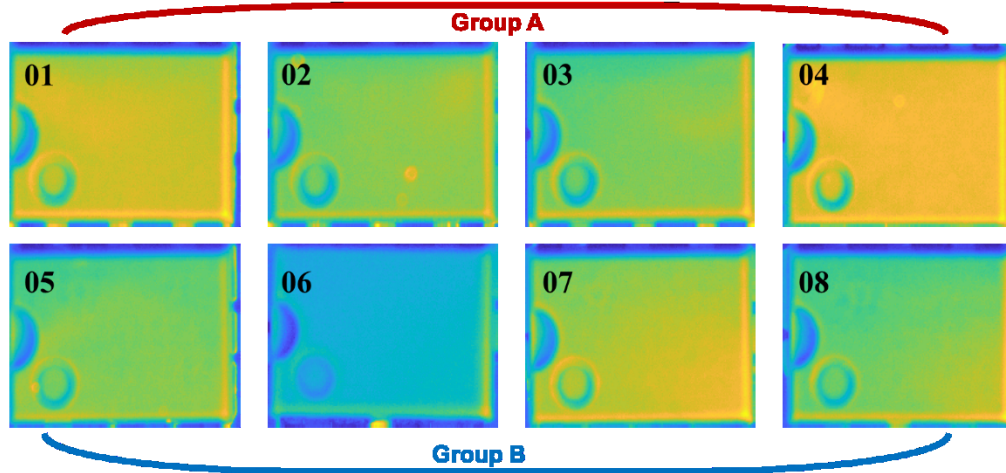


Figure 6 The first temperature frame (at 0.04s) after the flash.

Figure 7 shows the PCT images derived from the 1st to 6th EOF components in the full image scale, where very limited structural information can be observed. The 1st PCT image presents a noised single convex profile in the middle which may contain most die-related features. This observation indicates that the 1st SVD information should be focused on the proposed SWPCT reconstruction for die feature enhancement.

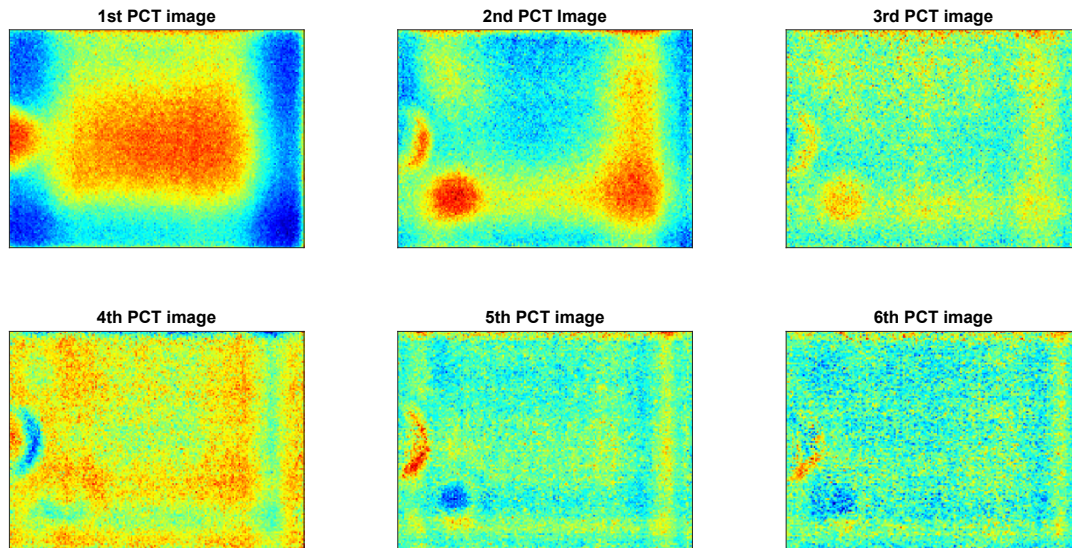


Figure 7 The first 6 orders PCT images decomposed by the full-scale SVD.

The proposed SWPCT reconstruction method is then applied to the 1st derivative of TSR data to achieve image enhancement. An ROI of the die shown in Figure 8 X-ray image (dot frame area) is extracted for further investigation in the below content. Figure 8 shows the SWPCT reconstructed image sequence (using a 17×17 pixels square window) of the ROI area, and the 1st PCT image extracted by SWPCT. The image contrast is effectively enhanced for the single convex profile in the die area, and the 1st PCT image from reconstructed data presents much less noise and better kurtosis. To compare the die structure presentation of the 1st PCT

from SWPCT, the results of chip 01 and 05 are shown in Figure 9, where the 1st PCT image from reconstructed images of two chips clearly indicates a kurtosis peak shifting with the same ROI. By plotting the horizontal profile and locating the peak of the centerline, the phenomenon of the horizontal kurtosis shifting complies with the structural shifting variation between two chips. Table 1 presents the horizontal coordinate peaks extracted from the 1st PCT images in Figure 9. It demonstrates that the enhanced results from the proposed SWPCT reconstruction improve the structural feature and can be used for the next structure reconstruction.

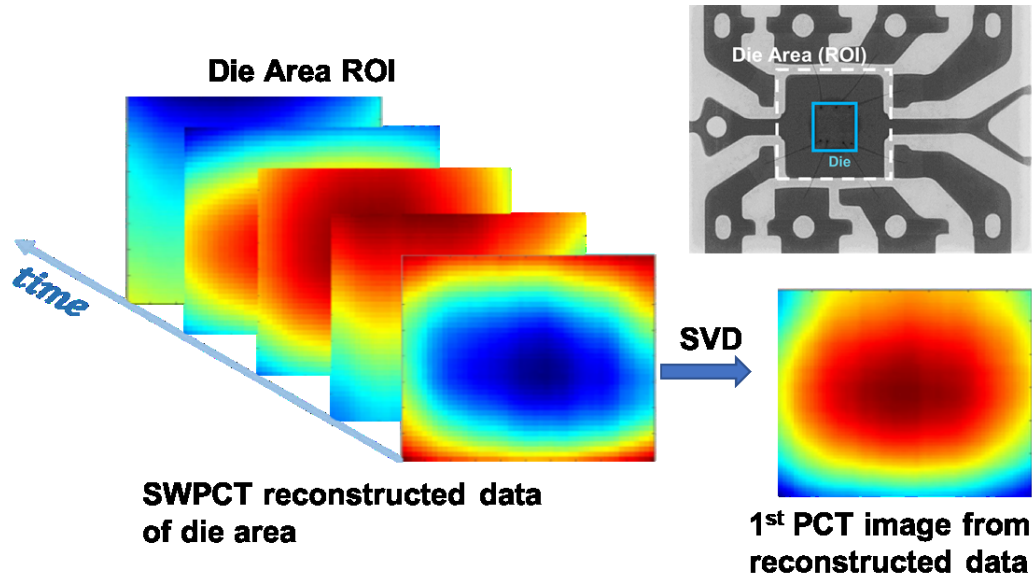


Figure 8 The 1st full image scale PCTs image based on SWPCT data

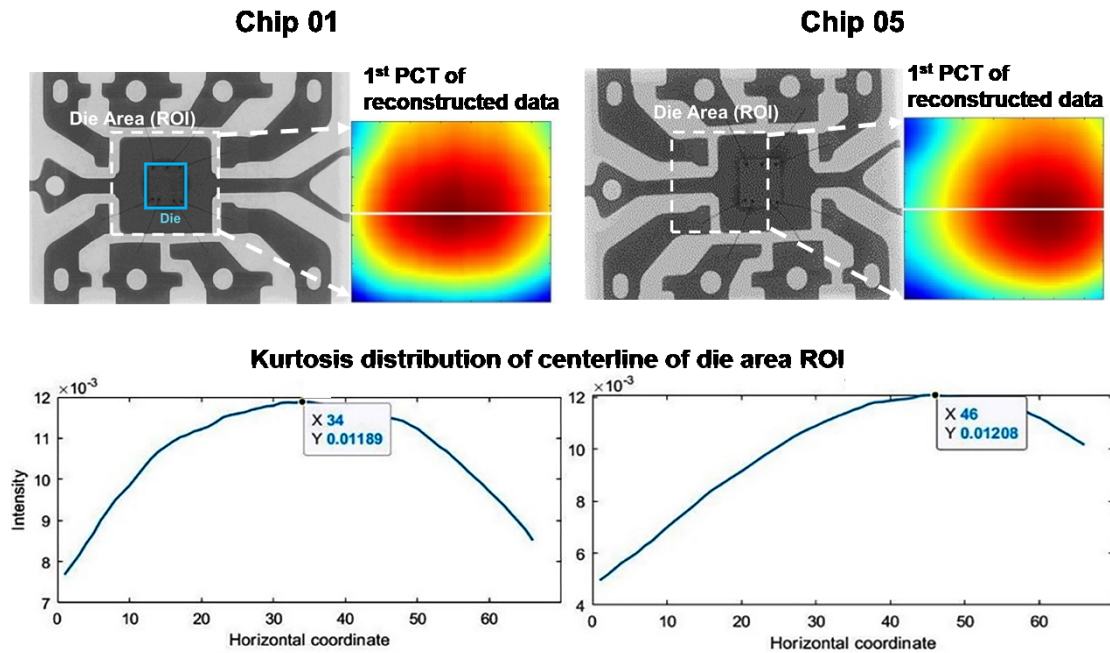


Figure 9 The kurtosis analysis of die and lead substrate area in SWPCT enhanced image.

Table 1 Kurtosis peak horizontal position of two group chips

Die Layout	Left				Right			
Chip No.	001	002	003	004	005	006	007	008
Peak horizontal Coordinates	34	36	32	28	46	42	49	52

3.2 Die reconstruction of the experimental data

For the feature image enhanced by the proposed method, a threshold-based boundary extraction method is employed to quantitatively reconstruct the position and dimension of the die and die substrate beneath it. It is composed of two main parts: threshold calibration and the reconstruction of the die boundary.

Firstly, the four chips of Group A were selected for calibration. The location of the die and die substrate were extracted from the X-ray image then mapped onto the feature image shown in Figure 10(a). The maximum peak value was extracted within each boundary and the average value of all pixels in the boundary was also calculated. The data for each die and die substrate is shown in Table 2, where the threshold is defined as the ratio of the average value to the maximum value. Based on the results shown in Table 2, the profile extraction thresholds were chosen as 94% and 80% for the die and die substrate, respectively.

Table 2 Threshold analysis using Group A samples for calibration

Item	Parameter	Chip001	Chip002	Chip003	Chip004
Die reconstruction threshold	Maximum Value	0.0111	0.0105	0.0111	0.0109
	Average Value	0.0106	0.0100	0.0104	0.0104
	Threshold	95.22%	95.86%	93.62%	95.34%
Die substrate reconstruction threshold	Maximum Value	0.0111	0.0105	0.0111	0.0109
	Average Value	0.0090	0.0086	0.0086	0.0087
	Threshold	80.92%	82.17%	77.70%	79.6%

Secondly, the feature images were processed into binary images based on the calibrated threshold. Then the Canny edge detection is employed to extract the boundary from the binary image. The extracted boundaries of die and die substrate were then mapped on the X-ray (see Figure 10(b)) to check its performance in terms of overlapping percentage.

Figure 11 shows the die and substrate boundaries overlayed on the X-ray images of Group A and B chips. The overlayed results demonstrate the feasibility of the proposed reconstruction method. The position of dies and substrates has good compliance with the ground truth in the

X-ray image. The proposed method can effectively identify the left and right die layout between two groups, although the dimension of the reconstructed die and substrate are slightly smaller than the actual size. This observation is potentially caused by two reasons. The primary reason is that the mould material of the two groups is different. Mould material affects the heat diffusion within EC and results in the variation of the spatial thermal pattern, especially on the kurtosis feature. The second factor is the lead frame layout, which is not entirely symmetric with the die horizontal shifting direction. The non-mirror symmetric variance of lead frame layout influences the locating accuracy of die and die substrate shifting due to the non-mirror symmetric thermal transfer in the lead frame area. Nevertheless, the proposed method effectively distinguish the die location and generally estimate the profiles of die and die substrate.

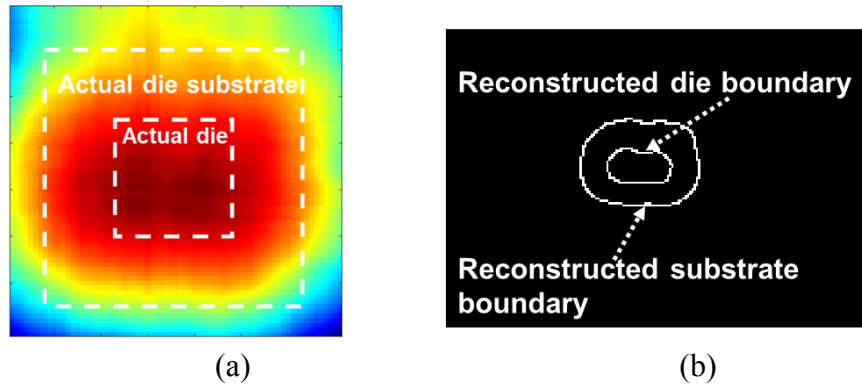


Figure 10 Boundary extraction using calibration threshold (a) Real physical area mapped on feature image of Chip 01; (b) Reconstructed boundary of Chip 01.

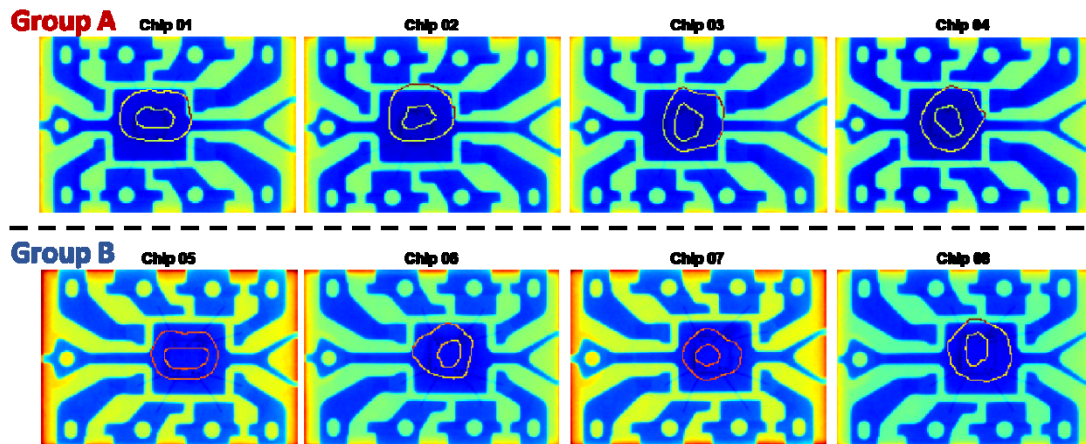


Figure 11 Fusion images of reconstructed die and substrate boundary with X-ray images

To furtherly demonstrate the enhancement of the proposed SWPCT, a comparison analysis between SWPCT feature image and traditional TSR, PCT is implemented using the Die ROI SNR defined in Figure 12. This SNR is calculated by the division of Die ROI and the background region surrounding the die substrate. This ROI SNR definition aims to describe the

contrast of the ROI region comparing to the background and are common used in Thermography inspection.

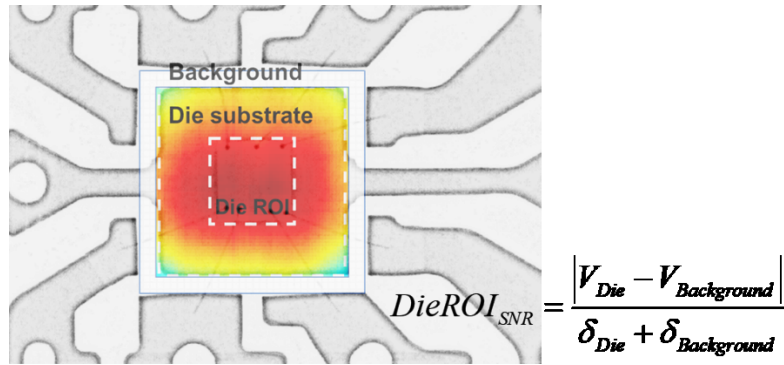


Figure 12 The Die ROI SNR definition

In Figure 12, the V_{Die} , $V_{Background}$ denotes the mean value of the Die ROI and Background region corresponding to below Fig. 1, respectively. And δ_{Die} , $\delta_{Background}$ denotes the standard deviation of the Die ROI and Background region, respectively. By comparing to traditional thermography post-processing in Table 3, the SWPCT remarkably improves the contrast of the die and reduce the noise level, and the effectiveness of SWPCT is validated.

Table 3 The Die ROI SNR comparison with traditional processing methods.

	$ V_{Die} - V_{Background} $	$\delta_{Die} + \delta_{Background}$	Die ROI SNR
TSR	0.0999	0.11238	0.8897
Traditional TSR+PCT	0.0039	0.0041	0.9512
SWPCT	0.0065	0.0037	1.7568

3.3 Lead frame layout identification of the experimental data

Based on the proposed SWPCT reconstruction method, the internal lead frame is also analysed. Compared to the 1st derivative data, the 2nd derivative TSR data is more sensitive to the local spatial thermal pattern. We selected the 2nd derivative TSR data as the input for SWPCT to detect the lead frame layout.

Figure 13 shows the process of feature enhancement for lead frame layout based on SWPCT. Instead of reconstructing back to the time domain in each window, the 3rd PCT data derived from the 3rd EOF of each window is employed to represent the internal lead frame feature. By consistent processing with Figure 5, the 3rd PCT based feature image for lead frame enhancement is selected as the feature image to reveal the hidden spatial information of the lead frame.

Figure 14 presents the features images of all chips in two groups. Although the feature image cannot fully reflect the lead frame details, parts of the feature images are in agreement with the actual lead layout. The area marked by the white dot rectangle at the image bottom is similar to

the lead layout in the X-ray image in the horizontal distribution. The convex spatial feature in the marked white dotted box region exhibits compliance with two bottom lead pins. This feature can be used to identify the lead frame layout.

It should be pointed out that the lead frame enhancement in Figure 14 is not capable to fully present the shape and dimension of lead pins. The influence factors are worthy of being discussed. As the PT is a reflection-based heat diffusion inspection method, the reconstruction of internal lead frame detail is affected strongly by the upper mould layer. As the mould layer has high thermal conductivity, the spatial SNR of the heat feature pattern in the lead frame layer will be quickly eliminated and hardly be captured from the surface. Another factor is that the selection of the sliding window size for lead frame enhancement should be furtherly optimised. The lead frame area contains more material discontinuity distributing from the middle to the edge of samples. The thermal feature of each lead frame part close to the die substrate area is an easily influenced area that affects by heat diffusion perturbation from the die, and is hard to be discriminated. A fixed sliding window size might not be suitable for this complex spatial feature enhancement scenario. A dynamic window size scheme should be competent for the lead frame feature extraction and will be investigated in the future.

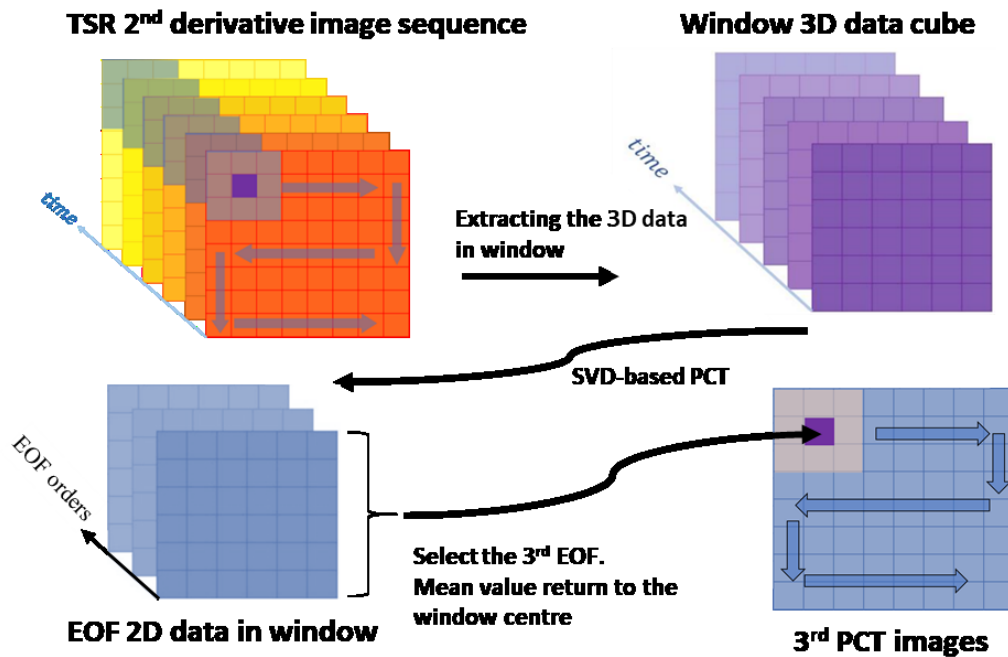


Figure 13 SWPCT reconstruction scheme for lead frame feature enhancement.

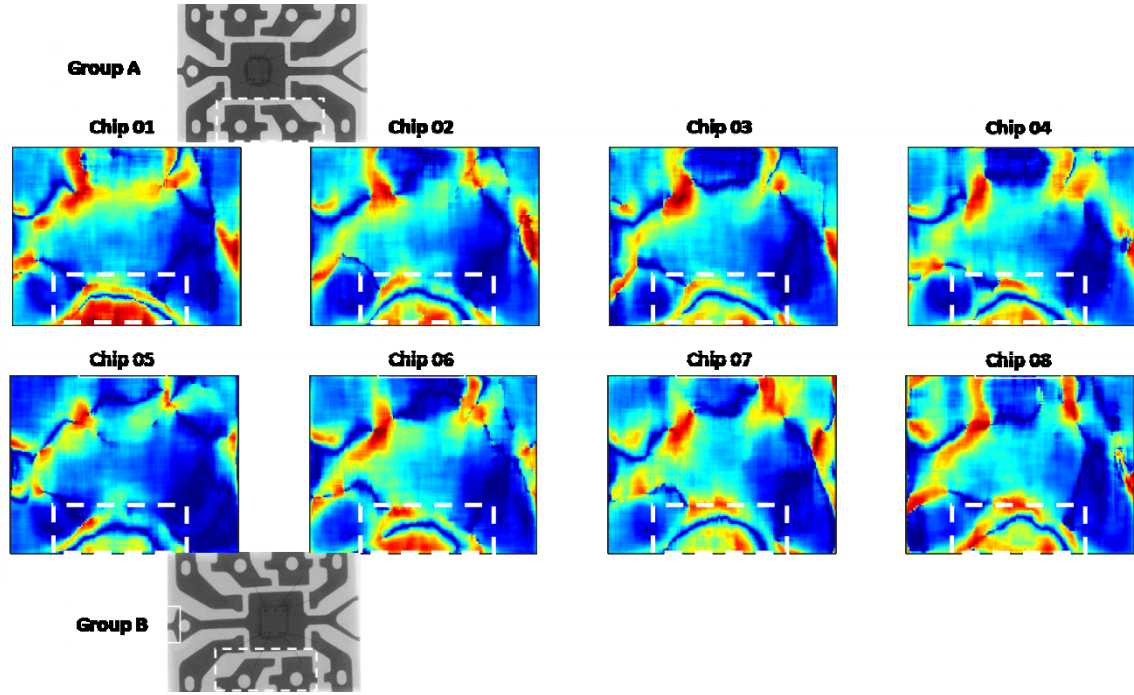


Figure 14 The 3rd order PCT images of SWPCT reconstruction of all samples with the corresponding X-ray image.

3.3 Simulation validation

To further validate the proposed method, simulation modelling is employed to predict the thermal signal of PT for ECs [27]. The simulation signals are then processed with the proposed method to demonstrate its ability to detect the layouts of die and lead frame.

The investigated ECs are a typical dual in-line packaged type composed of multiple layers with three primary materials: mould, lead frame and die. The X-ray images (see in Figure 2) provide a reference of the internal structure for simulation modelling of both verified and malfunctioning ECs. In this simulation, the distribution of the lead frame and die dimension in X-ray images were initially transferred to a binary mask. Then by mapping the mask onto the specific layers of the model, the real internal structure is modelled.

As a result, the established 3D models of Group A and B are presented in Figure 15, including the mould compound layers, the lead frame layer and the die layer. The thicknesses of the upper, lower mould, lead layer and die are 1.3, 1.5, 0.2 and 0.1mm, respectively. The model is surrounded by air material elements, and the pins connected to the lead frame are ignored. The whole model is discretised into $180 \times 120 \times 50$ units using the Hexahedral iso-parametric element. Homogenous materials were used for the mould, lead frame and die layers modelling. The heat flash in PT was simulated by a homogenous heat flux induction on the top surface of the model. The pulse peak of heat flux density applied on the surface elements was $5.0 \times 10^4 \text{ W/m}^2$. The material parameters of the model are shown in Table 4. The FEM theory and the pulse profile of the PT simulation are presented in the previous paper [22] in details.

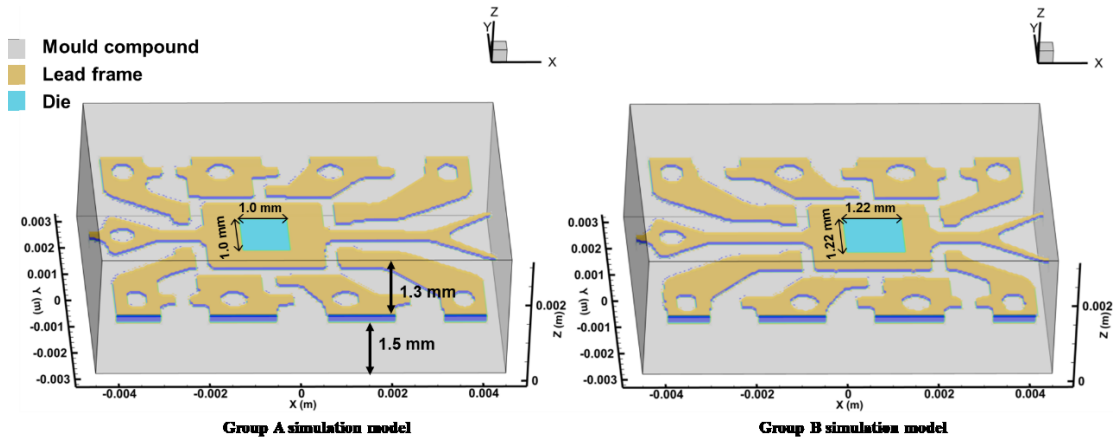
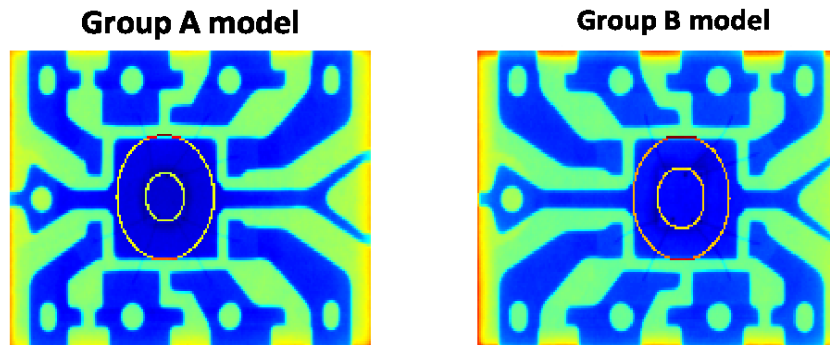


Figure 15 The established simulation models for Group A and B chips.

Table 4 Material thermal properties applied in the simulation.

Component (Material type)	Conductivity	Volumetric heat capacity
Mould compound (Resin)	5.40 W/(m·K)	1.33×10^6 J/K/m ³
Lead frame and pins (Copper)	3.85×10^2 W/(m·K)	3.45×10^6 J/K/m ³
Die (Silicon)	1.30×10^2 W/(m·K)	1.65×10^6 J/K/m ³

Figure 16(a) shows the reconstructed boundaries of the die and die substrate based on the simulation data. The reconstructed boundaries of die and die substrate are in agreement with the position and dimension of the actual structure. The length and width of the reconstructed die boundaries of simulation results are very close to the actual die even though the reconstructed circle shape is not the same as the rectangle ground truth. Figure 16(b) shows the enhanced feature images of the lead frame of the two models. The feature images clearly illustrate the lead frame layout variation and also each pin position. Not only the horizontal layout diversity can be easily observed, the thermal feature distribution effectively presents the location of each object in the lead frame. The simulation demonstrates the effectiveness of the proposed SWPCT method by presenting consistent structural enhancement.



(a)

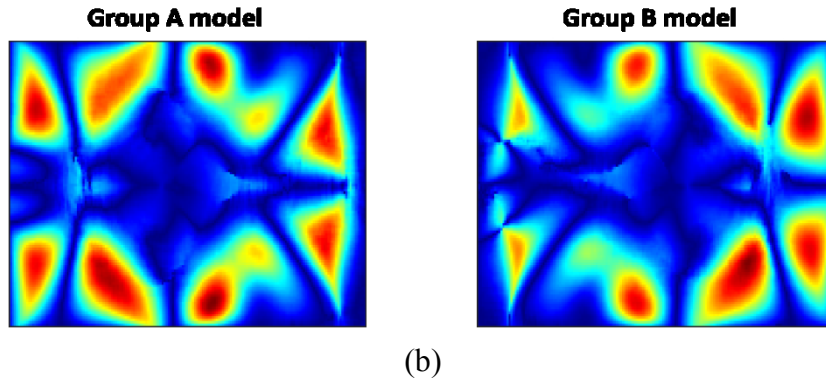


Figure 16 The produced results for the simulation data using the proposed method. (a) Reconstructed die and lead substrate boundaries of two models; (b) Feature images for the lead frame of two models

4. Discussion

When using the sliding window PCT to enhance the structure feature shown in Figure 5, a necessary discussion of the window size for the optimal enhancement should be implemented. An undersized window would lead to an insufficient SVD local data input and the incapability of spatial noise cancellation. An over-size window might contain excessive spatial information which reduces the spatial resolution of the local feature. By using different window sizes (d denotes the square window length) in SWPCT, Figure 17 shows the comparison of feature images from the reconstructed 1st PCT. On one hand, the results of a small window are not capable of neither improving image contrast nor reducing the spatial noise. On the other hand, a large window, such as 27 or 31 pixels, would lead to rectangular-shape distortion varying from the actual rectangular die and die plate. Therefore, proper window size should result in a feature image with a better kurtosis.

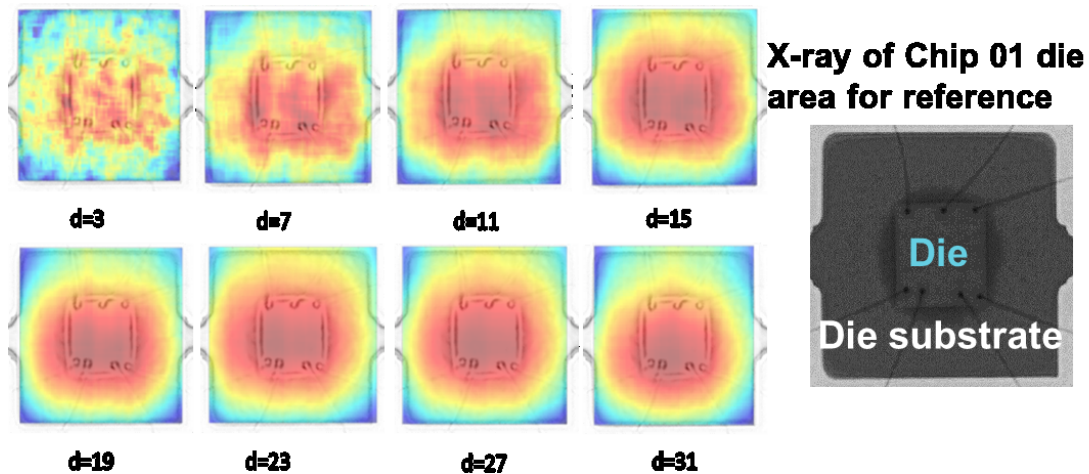


Figure 17 SWPCT feature images using different window sizes

To quantitatively analyse the proper window size, the rectangularity analysis is applied. A seventeen-level contouring process is used to convert the feature images in Figure 10 to standardised contour boundary, and the 3rd level contour was extracted. By referencing the fact

that the die plate substrate (see Figure 10 X-ray image) itself is a square with sharp edges, the rectangularity of the 3rd level contour was calculated using Eq. (11) and used to represent the result's resemblances to the real structure.

$$R = \frac{S_0}{S_{MBR}} \quad (11)$$

where R denotes the rectangularity of the selected contour boundary. S_0 is the area within the contour boundary and S_{MBR} is the area of the minimum bounding rectangle.

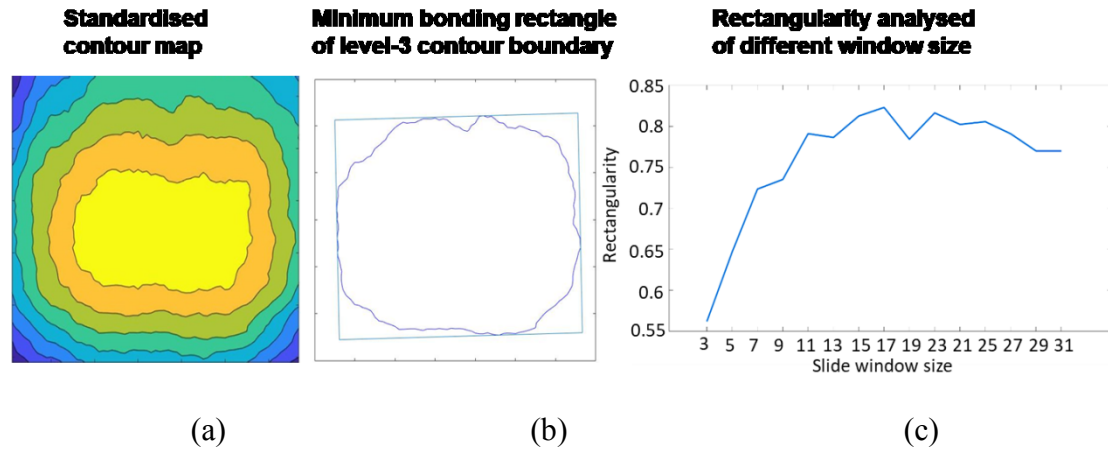


Figure 18 Standardised contour level for rectangularity analysis. (a) The seven-level contour map of $d = 17$; (b) Minimum bounding rectangle of level-3 contour; (c) The rectangularity of different window size.

Figures 18(a) and (b) present the standardised contour level feature image, and the minimum bounding rectangle of level-3 contour boundary when the window size d is 17 pixels, respectively; Figure 18(c) shows the rectangularity analysed for different window size. It shows that the best rectangularity occurs when the window size d is chosen as 17 pixels.

5. Conclusions

In this paper, a novel data analysis framework for enhancement and identification of the internal structure in the highly integrated electronic components using pulsed thermography was proposed. It firstly explores the application of a non-penetration technique (pulsed thermography) to identify key structure in the encapsulated ECs which is also suitable for fast batch screening. By equipping with a sliding spatial window on TSR and PCT, the proposed SWPCT reveals the thermal resistance of packaging mould material and enhances the sensitivity of spatial thermal features, which enables the possibility of identification structure layout by Pulsed Thermography (PT). Compared to the traditional PT image processing technique, SWPCT reduces the surrounding redundancy information by focusing on the selected window and therefore improves the spatial principal components sensitivity to the structure variation. By selecting an appropriate sliding window size, the SWPCT can extract and furtherly mark the hidden profiles of the die and die substrate. Similarly, it is able to identify the malposed lead-frame layout and eliminates the spatial and temporal noises at the same time.

The effectiveness of the proposed method has been successfully validated on two groups of typical OpAmps chip samples with internal structure diversity (X-ray observed). Further, a FEM simulation was applied to present a consistent conclusion. The proposed method shows its unique capability in inspecting internal structure in a complex structure, especially for the challenging of small but highly-integrated sealed components, which expands the applicability of PT and enriches the post-processing tools.

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Declaration of interests

☒ 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.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:



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