Internal defect identification method of TSV 3D packaging based on built-in integrated sensor

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Abstract
TSV (Through Silicon Via) is a key technology for three-dimensional (3D) packaging due to its unique vertical interconnection method. However, its particular manufacturing process often leads to internal defects, such as gaps, bottom voids, filling missing, which are usually difficult to be detected by common means. In order to discover the internal defect of TSV packaging effectively, a novel non-destructive inspection method based on built-in integrated temperature sensor array is proposed. The relationship between temperature distribution and internal defect is discovered and then corresponding sensor array layout is designed. The simulation analysis shows that this kind of sensor array can recognize the internal TSV defect. And supervised machine learning is used to construct the classification model by which different defects can be found and classified with relatively high accuracy, and the classification accuracy rate can reach 95.625%. Experiments were conducted and the rationality of this built-in sensing array was verified. The research provides a non-destructive testing method for TSV internal defects based on built-in-integrated sensors, and verifies the feasibility of sensor arrangement through simulation, laying a foundation for the realization of later TSV design optimization.

Keywords
TSV, built-in integrated sensors, GA-GRNN, internal defects

Date received: 13 June 2022; accepted: 3 August 2022
Handling Editor: Chenhui Liang

Introduction
As a key technology for 3D packaging, TSV has become increasingly important with its high performance and low power consumption. The basic idea of TSV is to interconnect devices by conducting vertically from chip to chip and the main function of TSV is signal transmission. The schematic diagram of the TSV 3D packaging structure is shown in Figure 1.1–4 Since TSV gradually develops toward smaller sizes, the scale effect is more obvious and the stress mismatch is more serious, resulting in defects such as bottom voids, gaps and filling missing.5–7 The existence of these defects can adversely affect the performance of electronic devices, reduce the reliability of the device, and even damage the device. As a result, it is critical to develop a method for accurately detecting internal defects.8,9

Much research has been done by many scholars and experts on the internal defects of TSV. Common TSV defect detection methods include scanning electron
microscopy (SEM) method, non-contact electrical detection method and X-ray detection method. SEM inspection method can effectively reveal defects inside the TSV 3D package structure and can locate and characterize small defects with feature sizes as low as 1 nm, but it need obtain cross-sections of the test objects and damages test samples, so it is often used as inspection tests. The contactless electrical test method is mainly used to obtain the electrical signal of the defective TSV output by applying the corresponding excitation, and compares it with the intact TSV output and the difference is amplified, thus defect detection can be realized. For further mastery the effects of short and open defects on the electrical of TSV channel, a non-invasive method of defects analysis on high-speed TSV channel is proposed. The method is demonstrated with S-parameter and time-domain reflectometry measurement results. And equivalent circuit models of defective TSV daisy-chain structures are presented, including the circuit components for open defect and short defect. With characterized dominant factor in each frequency range, S11 is analyzed to distinguish and locate the defects by the amount of capacitance, resistance, and inductance that the signal experiences. In recent years, post-processing algorithms, such as Machine Learning (ML) are widely used to implement defect classification. A supervised algorithm, such as random forest, is proposed to build classification models from trained S-parameters to detect defects such as voids and shorts in TSV-based 3D stereoscopic circuits that cannot be easily captured. Electrical inspection will usually be able to detect short-defect and open-defect that make changes in electrical parameters, greatly limiting the types of defects that can be detected. With the gradual reduction of critical dimensions such as TSV, X-ray has found great application in practical applications with its resolution below 15 nm. First, the detection image is captured by an X-ray detector, and the image is processed by image processing techniques, such as Canny operator and morphological modification, then a specific neural network model is trained by extracting the corresponding feature parameters. Finally, the trained classification model is tested using a small sample set, and the model is modified. The X-ray detection method has limitations such as human radiation and dependence on external equipment. Therefore, it is necessary to discover an environmentally friendly method that can detect a wide range of defects without the need for external equipment. Numerous studies have shown that during TSV fabrication and chip use, temperature changes occur due to mismatches in the coefficient of thermal expansion (CTE) of the materials used in the TSV structure. And it was found that the presence of defects inside TSVs leads to changes in the original heat dissipation pathway, which in turn affects the overall temperature distribution. Lau and Yue investigated the thermal performance of 3D integrated circuit packaging systems (SiP) with TSVs (through-silicon vias) based on heat transfer and CFD (computational fluid dynamics) analysis. Pan et al. demonstrated that the shape, size, and location of defects can have an impact on thermal stress; therefore, obtaining temperature variations can enable the identification and localization of defects. Due to the small chip size, temperature measurement methods mainly include on-chip temperature sensors; Chen et al. proposed a CMOS temperature sensor for on-chip thermal monitoring with a die area of only 14.8 μm × 22.2 μm. Sengupta et al. in 2017 proposed a compact nanoelectronic temperature sensor that is able to provide a higher throughput and lower energy consumption in comparison to state-of-the-art CMOS temperature sensors. This makes it possible in the near future to integrate the sensor into the TSV package at the beginning of the chip design, then it will be possible to obtain abnormal temperature signals inside the TSV package while avoiding contact, thus enabling the detection and identification of defects. A novel method for non-destructive detection of internal defects in TSVs is proposed. The temperature distribution is acquired online using a built-in sensing array to monitor the state of the TSV for defect detection.
detection; based on the ANSYS simulation validation, the temperature distribution data is analyzed using machine learning to determine the defect type. The arrangement of the built-in integrated sensors needs to be designed rationally, and there are various ways of arranging them. Using machine learning can quickly verify the rationality of the arrangement proposed in this paper. The schematic of the built-in sensor array is shown in Figure 2. The program flow chart is shown in Figure 3.

**Internal defect modeling and corresponding optimization of TSV packaging**

**Geometric model of TSV 3D structure**

By combining the actual process of TSV, the model can be simplified to facilitate thermal analysis and the design of the TSV interconnection structure. A rectangular chip module with an intermediate layer is selected, and the overall structure from top to bottom is as follows: a chip with silicon as the main raw material, a solder ball connecting the two layers between the chips and a filler layer (the main raw material is resin material and hereinafter referred to as the solder layer), a conductive copper pillar with a Si filler layer (hereinafter referred to as the TSV layer), and a substrate with bismaleimide triazine resin as the main raw material. In addition, to simulate the real structure of the chip when it is working, the top layer is a copper heatsink. The simplified model is shown in Figure 4.

Among the typical defects, the filling missing is shown in the finite element model as a complete absence of the internal copper column, and gap is shown as an incomplete filling of the copper column, and the bottom voids is shown as a partial absence of the bottom of the copper column.

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**Figure 2.** Built-in sensor array schematic.

![Built-in sensor array schematic](image)

**Figure 3.** The program flow chart.

![Program flow chart](image)

**Figure 4.** The simplified mode of TSV 3D model.

![TSV 3D model](image)
Finite element modeling and simulation analysis

After the application of a voltage load, the TSV interconnection structure is subjected to a thermo-electric coupling field due to changes in heat caused by the resistance and other parameters of the components. Therefore, internal defects in the TSV can be effectively identified by capturing the signal of the corresponding temperature change. After a schematic of each defect model of the TSV 3D package has been created, the thermo-electric module is selected for finite element simulation. In addition to setting the material according to the corresponding parameters, the same load is applied to each model. To simulate the real working environment, a sinusoidal AC voltage of 1.5 V is applied to the upper surface of the chip, and zero potential is applied to the bottom surface of the nine TSV copper pillars. At ambient temperature of 20°C, the convective heat transfer coefficient between surface of each part and air is 15 W/(m²·°C).

Table 1. Simulation dimensions and parameters.

|                  | Length/µm | Width/µm | Height/µm | Radius/µm | Thermal conductivity [W/(m·k)] | Resistivity (Ω·m) |
|------------------|------------|----------|-----------|-----------|-------------------------------|------------------|
| Copper pillar    | —          | —        | 300       | 100       | 390                           | 1.75e⁻⁸          |
| Silicon chip     | 400        | 400      | 300       | —         | 124                           | 1                |
| Substrate        | 700        | 700      | 300       | —         | 0.3                           | 0.1              |
| Solder           | 400        | 400      | 100       | —         | 57                            | 0.1              |
| TSV layer        | 400        | 400      | 300       | —         | 124                           | 0.1              |

Figure 5. (a) The results of tetrahedral meshing and (b) the results of hexahedral meshing.

Modeling optimization. In the process of solving by using element simulation, the whole model needs to be meshed first to get the basic cells and nodes that the finite element software can operate directly. The mesh division shape will have influence on the calculation results, and the current common mesh division cells are tetrahedral and hexahedral cells. To determine the mesh shape, finite element analysis was performed without changing the model and the number of cells, and only changing the cell shape. Figure 5 shows the mesh division results for tetrahedra and hexahedra, respectively, and the simulation results obtained are shown in Figure 6. From the obtained temperature distribution, it can be seen that the cell shape does not change the cloud shape, but the calculated values are changed. The highest temperature obtained for the tetrahedral is 110.84°C, as shown in Figure 6(a). And the highest temperature obtained for the hexahedron is 112.73°C, as shown in Figure 6(b). Since the detection accuracy of the built-in integrated temperature sensor...
is $\pm 0.2^\circ C$, 1.8$^\circ C$ caused by the cell shape has a great influence on the detection accuracy. According to the finite element theory, the accuracy of the first-order hexahedral mesh is higher than that of the first-order tetrahedral mesh, so the hexahedral element should be preferred.

**Cell size optimization.** The larger the element size is, the higher the calculation accuracy is, but the excessive number of cells affects the computational efficiency. To improve the computational efficiency while ensuring the computational accuracy, the cell size needs to be optimized. On the basis of the hexahedral cells is adopted, the intact TSV model is divided into 0.6, 0.7, 0.8, 0.9, 1, and 1.1 million node cells. Figure 6 shows the relationship between different nodes and slopes corresponding to the simulated maximum temperature.

It can be seen from Figure 7 that the slope of the highest temperature value corresponding to the node divided into 1 million and divided into 1.1 million is only 0.006. Therefore, 1.1 million nodes have high accuracy while ensuring computational efficiency.

**Simulation analysis**

After the shape of the divided mesh and the number of meshes have been determined, the corresponding loads and boundary conditions are applied and the temperature distribution of the defective TSV is obtained. Figure 8(a) to (d) show the temperature distribution of the critical layers of the intact TSV and defective TSVs interconnect structures, respectively.

It can be seen from Figure 8 that the temperature distribution of the TSV key layer in each defect model is obviously different from that of the intact TSV.

1. For the maximum temperature, it can be seen from Figure 8(a) and (c) that the TSV with filling missing shows the most significant difference (6.830$^\circ C$) with a maximum temperature of 117.510$^\circ C$; followed by the bottom voids TSV with a maximum temperature of 108.570$^\circ C$ and a temperature difference of 2.110$^\circ C$, as shown in Figure 8(d); while the TSV with gap has a maximum temperature of 110.49$^\circ C$ with the smallest temperature difference (0.190$^\circ C$), as shown in Figure 8(b).

2. From the temperature distribution, the intact TSV temperature distribution is uniform and
symmetrical; the filling missing TSV has an obvious tendency to be concave in the missing copper column; the gap TSV has a very similar temperature distribution to the intact TSV due to the small size of the defect; the bottom void TSV temperature distribution is shifted to the lower left corner as a whole, with the lowest temperature at the upper right corner.

Therefore, based on different temperature distribution phenomena, different defect forms can be identified, which provides a basis for TSV defect identification and location.

GA-GRNN based defect detection and classification

The external temperature characteristics caused by defects within the TSV 3D package structure are monitored, allowing defects to be effectively located and identified. On this basis, if the corresponding temperature sensors are arranged near the TSV area when preparing the chip, these sensors will be able to obtain the temperature information of the TSV under working conditions and complete the internal defect detection. The next problem is to determine the situation of putting the built-in sensors. Thus, we proposed a sensor layout and machine learning is used to realize the defect estimation and classification to verify the layout rationality.

Considering that the amount of data used is small and the classification model is relatively simple, the GRNN (General Regression Neural Network) with faster training speed is used to determine the arrangement of the built-in integrated temperature sensors. Because the smoothing factor $\sigma$ in GRNN is difficult to determine, which affects the modeling accuracy and model generalization ability, GA (Genetic Algorithm) is used to optimize the smoothing factor $\sigma$ in GRNN. The algorithm simulates the law of natural selection through multiple selection, crossover and mutation, so that the objective function tends to the optimal value. In addition, the algorithm has strong global

Figure 8. (a–d) The key layers temperature distribution of intact TSV, gaps TSV, filling missing TSV, bottom voids TSV, respectively.
optimization ability and strong adaptability. The result is simple and easy to implement.23,24

GA-GRNN method

The smoothing factor $\sigma$ of GRNN is optimized by GA, and the classification accuracy of the sample data is used as the criterion to determine the best smoothing factor. In GRNN, suppose the joint probability density function of random variable $x$ and random variable $y$ is $f(x,y)$, then the predicted output of $\hat{Y}$ under the condition of input $X$ is,

$$\hat{Y} = E(y|X) = \frac{\int_{-\infty}^{\infty} y f(X,y)dy}{\int_{-\infty}^{\infty} f(X,y)dy}$$  \tag{1}

For the unknown probability density function $f(x,y)$, it can be obtained from the non-parametric estimation of the observation samples of $x$ and $y$, where, $X_i$, $Y_i$ are the sample observations of $x$ and $y$, respectively; $n$ is the sample size; $p$ is the dimension of the random variable; $\sigma$ is the smooth factor.

$$f(X, Y) = \frac{1}{n(2\pi)^{p/2} \sigma^p} \exp \left[ -\frac{A^T A}{2\sigma^2} \right] \exp \left[ -\frac{B^2}{2\sigma^2} \right]$$  \tag{2}

Where, $A = X-X_i$; $B = X-Y_i$. Bringing $\hat{f}(X,Y)$ instead of $f(X,Y)$ into equation (1) and exchanging the order of integration and summation, we get:

$$\hat{Y} = \frac{\sum_{i=1}^{n} \exp \left[ -\frac{A^T A}{2\sigma^2} \right] \int_{-\infty}^{\infty} y \exp \left[ -\frac{C^2}{2\sigma^2} \right] dy}{\sum_{i=1}^{n} \exp \left[ -\frac{A^T A}{2\sigma^2} \right] \int_{-\infty}^{\infty} \exp \left[ -\frac{C^2}{2\sigma^2} \right] dy}$$  \tag{3}

Where, $C = Y-Y_i$. Since $\int_{-\infty}^{\infty} z e^{-z^2} dz = 0$, an operation on equation (4) yields,

$$\hat{Y}(X) = \frac{\sum_{i=1}^{n} \hat{Y}_i \exp \left[ -\frac{A^T A}{2\sigma^2} \right]}{\sum_{i=1}^{n} \exp \left[ -\frac{A^T A}{2\sigma^2} \right]}$$  \tag{4}

In equation (4), the estimated value $\hat{Y}(X)$ is the weighted average of all sample observations $Y_i$, and the weight factor of each observation $Y_i$ is the exponent of the square of the Euclidean distance between the corresponding sample $X_i$ and $X$. If the smoothing factor $\sigma$ is large, then $[(X-X_i)^T(X-X_i)]/2\sigma^2$ tends to 0, and the estimated value $\hat{Y}(X)$ is approximately equal to the mean of all sample dependent variables; on the contrary, if the smoothing factor tends to 0, the estimated value $\hat{Y}(X)$ will be very close to the training sample. When the points to be predicted are included in the training sample set, the predicted value of the dependent variable obtained by equation (4) will be very close to the corresponding dependent variable in the sample. Once the points that are not included in the sample are encountered, the prediction effect may be very poor, which is called over-fitting.

Therefore, we know that the error between the output data and training samples of the GRNN is mainly determined by the smoothing factor. Therefore, the GRNN has a very simple performance control method, and better performance can be obtained by adjusting the smoothing factor. GA (Genetic Algorithm) with global random search capability is used to optimize the smoothing factor $\sigma$ in GRNN. For convenience, the Generalized Regression Neural Network (GRNN) optimized by Genetic Algorithm (GA) is expressed as a GA-GRNN model.

The GA introduces the biological evolution principle of “survival of the fittest” in nature into the group formed by optimized parameters and calculates the fitness value of each individual according to the fitness function. Individuals are screened through operations such as selection, crossover, mutation, etc., and individuals with low adaptability are eliminated, and individuals with high adaptability are retained, thereby generating a new generation of groups. Repeat the cycle until the conditions are met.

The Genetic Algorithm is used to search for the optimal smoothing factor, and the GA-GRNN model is established. The specific steps are as follows:

1. Normalize the preprocessing of the data. The training data is normalized using the Min-Max Normalization function, and the data is distributed between $[0,1]$. The conversion function is

$$P = \frac{P - \min P}{\max P - \min P}$$

2. Determine the genetic algorithm parameters.
3. The genetic algorithm is initialized, and the initial population $P(g)$ of GRNN smoothing factor is generated, and the evolution algebra $g = 0$.
4. GRNN reads learning samples for network training, and performs fitness evaluation according to the given fitness function. The fitness function here is the ratio of the number of correctly classified test samples to all test samples.

$$\text{fitness} = \frac{T_R}{T}$$

Where, $T_R$ is the number of accurately classified test samples, and $T$ is the number of all test samples.
5. The genetic algorithm performs selection, crossover and mutation operations according
to the fitness of each individual to obtain a new population \( P(g + 1) \), and the evolutionary algebra \( g = g + 1 \).

(6) Determine whether the maximum evolutionary algebra has been reached, if it has been reached, stop the calculation and return to the individual with the highest fitness; otherwise, go to step (4) until the maximum evolutionary algebra is reached.

(7) Output the real-valued number corresponding to the individual with the highest fitness, which is the optimal smoothing factor;

(8) Establish a GRNN model with the optimal smoothing factor \( \sigma \), make predictions on the test samples, and get the prediction results.

(9) De-normalize the predicted data and evaluate the performance of the GRNN network.

The flow chart of the model is shown in Figure 9.

**GA-GRNN analysis**

The 6 equal points of the diagonals and midlines of the TSV key layer are used as added positioning of the sensor (it will not be processed in actual processing), and the built-in integrated sensors are located as shown in Figure 10. And the eight collected temperature values (in °C) used as the characteristic values in the GRNN model.

The characteristic point temperature values of intact TSV and defective ones were obtained by varying the surface heat transfer coefficient, where the surface heat transfer coefficient ranged from 10 to 15 W/(m²·°C) in steps of 0.02. Taking the intact TSV as an example, the temperature distribution of the surface heat in the range of 10–15 W/(m²·°C) (in steps of 0.02) was first obtained.

A total of 100 sets of intact TSV temperature distribution were obtained and corresponding data were collected. Similar to the intact TSV sample data extraction method, sample data for gaps TSV, bottom voids TSV, and filling missing TSV were obtained, for a total of 300 (3 × 100) sets of defective TSV sample data.

All the sample data (400 groups) were divided into training and test sets in the ratio of 3:2, and the sample data were classified into four types: intact TSV, TSV with gaps, TSV with bottom voids, and TSV with filling missing.

**Analysis result**

The maximum number of genetic iterations of the GA is set to 50, the number of chromosomes is 50, and the range of smoothing factor \( \sigma \) increases from 0.1 to 2,
with an increase of 0.1; roulette wheel selection, single-point crossover and two-point swap are used in selection, crossover and mutation operations, respectively. The crossover probability is 0.4, and the mutation probability is 0.2. The chromosomes are initialized and the maximum value of the fitness function is obtained when the smooth factor \( s = 0.694 \) through continuous training, which can be known as the optimal result obtained by genetic optimization. In Figure 11, the ordinate represents the number of iterations, and the abscissa represents the highest value of the fitness function of the individual in each generation. Figure 11 shows that the algorithm tends to a constant classification accuracy for the sample data after 50 evolutionary algebra and the classifier performance reaches the optimal state, that is, the fitness value reaches the highest.

In the training process of the GRNN model, the value range of the smooth factor is also set to \([0.1, 2]\), and the experiment is repeatedly cycled by the interval distance \( \Delta \sigma = 0.1 \), and the best fitting effect is obtained when the best smooth factor \( \sigma = 0.5 \). The test classification effect of GRNN is shown in Figure 12(a). The tested classification effect of GA-GRNN is shown in Figure 12(b). The abscissa of Figure 12(a) and (b) is the number of test samples, and the ordinates 1, 2, 3, and 4 represent filling missing TSV, gaps TSV, bottom voids TSV, and intact TSV, respectively. It can be seen from the comparison of the classification effects of the two models on the test samples in Figure 12(a) and (b).

1. In terms of classification accuracy, the generalization ability of the GRNN model needs to be improved compared with the GA-GRNN model, and the classification accuracy needs to be improved, too. The classification accuracy of the GA-GRNN model on the test samples is higher than that of the GRNN model. And The classification accuracy rate of the GA-GRNN model is 95.625\% while that of the GRNN model is only 87.500\%.
2. From the value of the smoothing factor, the values of the smoothing factor obtained by the two methods can be seen to be the best value globally by using the GA; when the cyclic calculation method is used, the value has

![Figure 11](image1.png)  
**Figure 11.** Relationship between the evolutionary algebra and fitness value.

![Figure 12](image2.png)  
**Figure 12.** Test results: (a) GRNN test results and (b) GA-GRNN test results.
certain limitations, which reduces the accuracy of the model.

(3) In terms of computational efficiency, the GRNN model ran longer than the GA-GRNN model with the same computer configuration (i5-10400 cpu). The GRNN model needs 23.219s, while the GA-GRNN model needs 22.547s, with more efficiency.

Therefore, the accuracy of GA-GRNN model classification proves the rationality of the arrangement of built-in integrated sensors and the effectiveness of the method for detecting and identifying internal defects in TSV.

Experimental verification

Sample preparation

In the preparation process of TSV 3D packaging, due to the immature processing technology, uneven filling of copper columns in TSV often occurs. Because the copper column of intact TSV is tightly combined with silicon chip, it has little effect on temperature propagation. Therefore, without affecting the research, the manufacturing process of the sample is simplified, and the holes can be directly prepared on the silicon wafer to simulate various defect forms. To ensure the accuracy and rationality of the experiment, the sample size should be consistent with the simulation size. Among them, the intact TSVs can be regarded as a complete silicon wafer. Gaps TSVs can be seen as etching holes of corresponding sizes on silicon wafers. The bottom voids TSVs can be seen as blind holes with a certain

Figure 13. The backside local magnification of a single TSV sample.

Figure 14. Experimental schematic: (a) schematic diagram of experimental system and (b) physical map of the experimental system.

Figure 15. Temperature distribution of intact TSV and defective TSVs: (a) intact TSV, (b) missing filling, (c) gaps, and (d) bottom voids.
size etched on the silicon wafer. Filling missing TSVs can be seen as etching holes in silicon wafers. The preparation of TSV samples is mainly aimed at the structure, size parameter design, production process and sample cutting method. The TSV three-dimensional package structure integrates two main parts: the chip layer and the TSV layer. The TSV layer integrates the substrate layer and the solder layer, and the corresponding dimensional parameters are as follows: TSV layer length $T_1 = 7 \text{ mm}$, width $T_2 = 7 \text{ mm}$, thickness $H_1 = 300 \mu\text{m}$; chip layer length $T_3 = 4 \text{ mm}$, width $T_4 = 4 \text{ mm}$, thickness $H_2 = 300 \mu\text{m}$; TSV copper pillar radius is $100 \mu\text{m}$; this structure is consistent with the previous simulation structure and related dimensional parameters.

The preparation steps are as follows. (a) A TSV sample mask is designed on a complete wafer to expose the TSV copper column in the upper right corner to construct defects. Figure 16 shows the backside local magnification of a single TSV sample. (b) In order to design the through hole and blind hole in the three defects, the laser etching method with high efficiency is adopted by adjusting the width and depth of the etching. (c) For the cutting of TSV samples, since the sample size is micron, the spacing of a single sample is very small and it is very easy to scratch. Therefore, the picosecond laser method is adopted. The physical map of a single sample after cutting is shown in Figure 13. The above preparation steps not only simplify the processing process, but also ensure the quality of the test sample.

Experimental principles

The schematic diagram and physical diagram of the experimental system are shown in Figure 14. The test sample was placed on the XH-RB3825 small high temperature ceramic heating rod, and the DC voltage regulator was connected to the positive and negative poles of the heating rod. In order to be consistent with the simulation, the voltage regulator provided 1.5 V potential. After a period of time, the temperature was transferred to the TSV 3D packaging sample. At the same time, the temperature information of the TSV sample was captured by the FLIR T630 infrared thermal imager, and the temperature measurement value of the infrared thermal imager was observed. After the temperature of the sample was stable, the temperature image was recorded. Finally, the obtained temperature information was transferred to the processing terminal and analyzed in more detail by the relevant professional image processing software, such as the temperature value, maximum temperature value and minimum temperature value at any point in the image.

Experimental results and analysis

By applying an external load consistent with the simulation, infrared thermal images of the three defect TSVs can be obtained, as shown in Figure 15. The temperature distribution of normal TSV (Figure 15(a)) gradually decreases from the center to the surrounding temperature, and the shape is symmetrical; the temperature field distribution of the filling missing TSV (Figure 15(b)) shows a significant depression in the temperature at the defect TSV copper pillar in the upper right corner; due to the lack of a small amount of copper material, the heat dissipation path is hindered, resulting in an increase in thermal resistance, the temperature field distribution of the gaps TSV (Figure 15(c)) has a red ring with a smaller diameter and higher temperature appears in the upper right corner; the temperature field distribution of the bottom voids TSV (Figure 15(d)) is due to the lack of some copper material at the bottom of the copper pillar, and a red ring appears in the upper right corner, with a diameter comparable to the size of the copper pillar. The experimental results are in good agreement with the simulation conclusions, and the internal temperature distribution law can achieve the detection and identification of typical defects of TSV.

The infrared heat distribution maps of defective TSVs were obtained by FLIR Tools for analysis, and the temperature data corresponding to the position of the built-in integrated temperature array proposed in Section 4.2 was obtained and used as the feature value in the GA-GRNN classification model for classification tests, and the classification result is shown in Figure 16. There were 16 sets of test data, and labels 1, 2, 3, and 4
represented filling missing, gaps, bottom voids, and intact TSV, respectively, with a classification accuracy of 93.75%. The gaps TSVs were not all correctly classified because the defect size was small and the temperature regular was more similar to that of intact TSVs, and this conclusion was consistent with the simulation analysis.

Conclusion

An integrated sensor array is used to achieve internal defect detection in TSV 3D packaging and the detection validation is proved by simulation analysis and experiments. A recognition and classification model based on GRNN optimized by Genetic Algorithm is developed. The simulation results show that three typical defects inside the TSV can be effectively identified, and the defect classification accuracy is 95.625%. And the rationality of this sensor array arrangement is verified by experiments with the 93.75% classification accuracy. Compared to the existing inspection methods, such as optical inspection methods, need to destroy the test sample to observe its cross-section or internal image, which will cause additional damage to the test sample during the inspection process; X-ray inspection methods have higher detection resolution but depend on external equipment and lower detection efficiency; machine learning using S-parameters to build classification models can only distinguish open and short-circuit defects, and detect defect types are more single. The method proposed in this paper can achieve real-time, online, active detection and identification of multiple types of defects.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the National Natural Science Foundation of China (Grant No. 51975191 and 51805154), Green Industry Technology Leading Project of Hubei University of Technology (XJ2021004901) and Scientific Research Foundation of Hubei University of Technology (GCRC 20200010). Project of Xiangyang Industrial Institute of Hubei University of Technology (XYYJ2022B01).

Data availability statement

The data used to support the findings of this study are available from the corresponding author upon request.

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