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The PCB Weld Joint Point Cloud Reconstruction Based on Improved Interpolation Techniques

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***Abstract*—Weld joints are vital portions that support electronic components, and detecting defects in weld joints is a critical step in ensuring the stability and dependability of electronic goods. Because the 3D point cloud can obtain important height information of printed circuit board (PCB), and the scanning environment is not easily affected by light, the weld joint defect detection based on point cloud deep learning is widely used in PCB. However, due to the imaging characteristics of the 3D camera, the substrate in the PCB point cloud is dense and the weld joints are sparse, resulting in the model not being able to fully learn the feature information. In order to overcome this problem, this paper analyzes the distribution pattern of PCB point cloud in Z coordinate through histogram, locates the segmentation of substrate and weld joints, improves the nearest neighbor interpolation algorithm, and proposes a weld joints Interpolation algorithm (Weld Joints Nearest Neighbor Interpolation, WJ-NNI), which can fill the sparse region of weld joints, increase the number of point clouds of weld joints, improve the problem of uneven distribution of PCB point clouds, and improve the accuracy of the model for the segmentation of weld joints, and the effectiveness of the algorithm is verified on the homemade dataset.**

Keywords*—*printed circuit board, point cloud interpolation, point cloud segmentation, weld joint detection

I. Introduction

The quality of the printed circuit board (PCB), an essential critical connection in contemporary electronic in-formation goods, directly influences the efficiency and dependability of products. Therefore, any PCB defect should be identified promptly and precisely to avoid a product failure while it is in use.[1] . The PCB manufacturing process is time-consuming, and the high-density and high-integration manufacturing requirements result in a variety of surface manufacturing faults that have a significant impact on product quality, therefore weld joint quality is critical in this process[2] .

Image-based PCB inspection technologies, such as classic Automated Optical Inspection (AOI), are extensively employed in PCB manufacturing, however they are prone to false alarms or omissions in the detection of complex faults. In comparison, the YOLO framework is more reliable in recognizing objects in photos and has produced superior results in PCB flaw identification. Although the image-based method has achieved better results in the detection of weld joint defects, it depends heavily on the illumination system, which is expensive due to the high precision camera and strict lighting equipment requirements. In addition,2D image representation of 3D objects may lead to a lack of 3D geometric information.The highlight of our work is the use of 3D point clouds to detect weld joint defects with 3D point clouds acquired from a binocular lidar system. Importantly, 3D point clouds may give detailed geometry, shape, and scale information, allowing 3D objects to retain their original geometric information in 3D space.On the other hand, lidar capture of point clouds is resilient to light change, eliminating the need for sophisticated illumination systems. Furthermore, with the development of low-cost scanners, point clouds have demonstrated strong potential for 3D object flaw identification[2] .Small deformations on the PCB surface, particularly in high-density integrated circuits, can have an impact on electrical performance, making high-precision 3D point cloud data gathering and processing crucial.

Although the point cloud data can improve the accurate three-dimensional information of the object, due to the 3D camera imaging characteristics, and the PCB substrate and weld joint material and other factors, the PCB point cloud obtained by scanning with the 3D camera is characterized by a dense substrate and sparse weld joints. Due to this characteristic, the PCB data is fed into the 3D point cloud model, and the model is not sufficient to extract important weld joint information, which affects the subsequent weld joint inspection and quality analysis[3] .

Interpolation methods for point cloud include traditional point cloud interpolation methods and deep learning-based interpolation methods, but the existing point cloud interpolation methods cannot PCB point cloud distribution is uneven, because these interpolation methods will be interpolated on the PCB point cloud as a whole, the substrate and the weld joints point cloud will be interpolated, and the distribution of the two is still uneven.

To solve the aforementioned issues, this study provides a novel interpolation approach that only interpolates the weld joint region in the PCB point cloud, therefore mitigating the problem of uneven substrate and weld joint distribution. The primary contributions of this study are as follows:

1) The distribution law of the PCB point cloud on the Z-axis is evaluated using a histogram to calculate the intersection line of the substrate and weld joints, which is then utilized to enhance the closest neighbor interpolation technique and propose the weld joint interpolation methodology. The

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algorithm can fill in the sparse areas of weld joints and extend the critical information of weld joints.

2) To assess the algorithm's efficacy, a PCB weld joint segmentation dataset was gathered and created using a 3D laser scanner..

II. RELATED WORKS

A. Point Cloud Interpolation Methods

Point cloud interpolation is a vital task in point cloud data processing because it aims to infer continuous surface or spatial features of a region in space from discrete point cloud data[4] .In general terms, interpolation methods aim to establish a weighting function to predict values at unsampled locations, based upon measured values in the same general vicinity[5] Point cloud data are often collected using 3D scanning, LiDAR, and other devices, and they are generally sparse, irregular, and noisy[6] . As a result, determining how to correctly interpolate from incomplete or irregular data has emerged as a key research question in point cloud processing[7] .

Common point cloud interpolation methods include Nearest Neighbor Interpolation (NN)[8] ,Thin Plate Spline Interpolation (TPS)[9] and Inverse Distance Weighted Interpolation (IDW) [5]. IDW and NN are similar in that they are local interpolators: they estimate values based on the k-closest sampled locations, with no projected values beyond the sampled value range. TPS, on the other hand, belongs to the class of algorithms known as spline-based or Radial Basis Functions (RBF). These attempt to provide a surface with minimum tension in order to mitigate the effects of sample measurement mistakes. TPS is a global interpolator, which means that all known values are used to anticipate each value, and predictions do not necessarily fall inside the range of sampled values. Among the common point cloud interpolation algorithms, NN is the simplest and fastest interpolation method.

The majority of existing point cloud interpolation methods are aimed at interpolating point clouds with complex shapes and features such as complex terrain, landforms, vegetation interpolation, and 3D modeling[4-6], whereas the structure of PCB point clouds is relatively simple and does not require complex and high interpolation algorithms, and due to the industrial requirements, which need to be detected for a large number of PCBs in a limited amount of time, a simple and This study uses NN as a benchmark to enhance the interpolation technique.

B. 3D Network Model

Models of 3D point cloud data are separated into two categories: network models that process point clouds indirectly and network models that process point clouds directly[10] . The first group of approaches, such as translating point clouds into voxel meshes[11] or multi-view based models[12] ,minimizes computing complexity but may lead to loss of information. As a result, network models have arisen that analyze point clouds directly, preserving the structural information of the original data. PointNet[13] is the first novel network to process raw point clouds, addressing the issue that typical convolutional neural networks (CNNs) cannot handle unorganized and unstructured input. PointNet++[14] is an upgraded version of PointNet that works by switching from local to global feature extraction, compensating for PointNet's limitations in local geometric processing.

III. METHODOLOGY

A. PCB Point Cloud Characterization

3D laser imaging works by projecting a laser line onto an object's surface, then capturing and analyzing the reflected light to determine the object's three-dimensional structure. When scanning PCBs, weld connections frequently have considerable curved surface differences, resulting in dispersed and uneven reflected light that is difficult to capture by camera. In contrast, substrate surfaces are flat, so reflected light is concentrated and easy to collect. As a result, based on the 3D profiler's scanning characteristics, the point cloud density is larger in the PCB substrate section, while it is sparser in the weld junction region due to the weak reflected light.

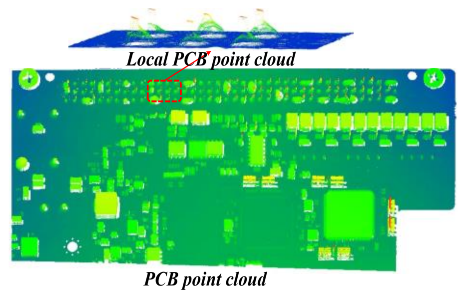

Fig 1 PCB point cloud diagram

The enlarged Local PCB point cloud in the above Fig 1 shows that the substrate point cloud is dense but the weld joints point cloud is sparse, which will limit the model's ability to detect and recognize weld joints due to the point cloud's imbalanced distribution.

CloudCompare includes a histogram analysis tool that takes the Z-coordinate of the point cloud as the horizontal coordinate and the frequency as the vertical coordinate. Adjust the crossbar range such that when the crossbar surpasses the peak value, the substrate section becomes gray, but the weld joints and other components retain their color, as shown in the Fig 2 below. The histogram allows you to treat the substrate and weld junctions individually. In this research, we use the histogram to find and interpolate the weld joint section in order to tackle the problem of uneven distribution of the PCB point cloud.

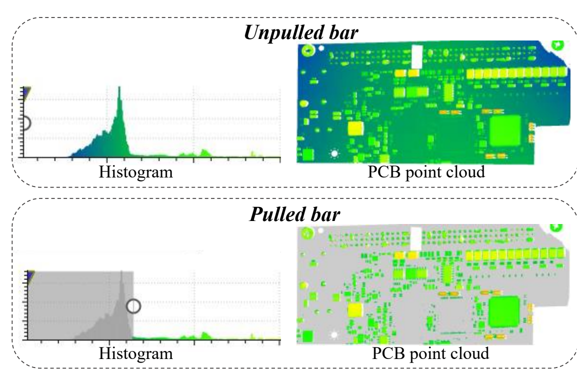

Fig 2 Histogram point cloud correspondence plot

B. Histogram-based PCB Point Cloud Analysis

To accurately analyze the distribution of the PCB point cloud in Z coordinate with histogram, it is necessary to process the PCB as shown in the Fig 3 below. First, remove the conveyor belt point cloud and other miscellaneous points. Because the PCB point cloud scanned by the 3D profiler occupies a lot of space and contains hundreds of millions of points, it is impossible to deal with it directly with the model, so it is also necessary to cut the PCB into small The collection consists of 490 PCB point cloud files.

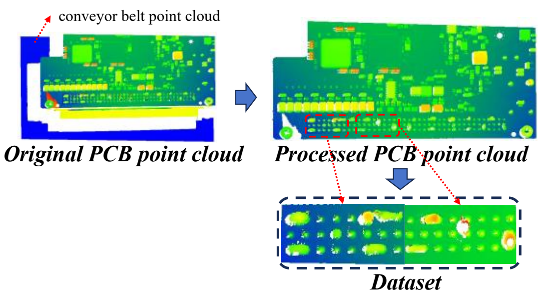

Fig 3 PCB point cloud processing flowchart

This study uses an experiment to reduce the right side of the peak to 0.2*peak at the matching horizontal coordinates (Z value) for the segmentation line's substrate and weld connections. If a Z coordinate point is greater than the segmentation line, it corresponds to the weld joints point cloud, otherwise to the substrate point cloud. As a result, the Segmentation line may separate the weld joint point cloud from the PCB point cloud, and the interpolation technique can be used to the weld joint cloud to increase the number of weld joint point clouds, as seen in the Fig 4 below, which depicts the entire analysis process.

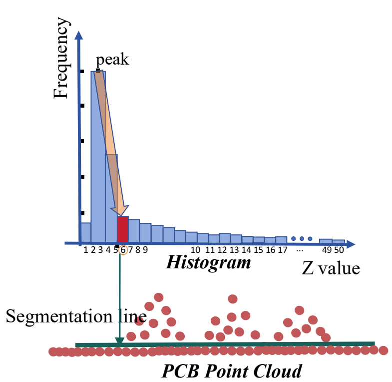

Fig 4 Histogram-PCB point cloud analysis diagrams

Three PCB point cloud files are randomly selected from the data set, and the above method is used to find the segmentation line. The points with Z coordinate ≥ *Segmentation line* are assigned blue color, and the points with Z coordinate ≤ *Segmentation line* are assigned red color. This shows that the substrate and welded joints can be more accurately separated by the color of the Fig 5, and also shows that the histogram At the same time, it demonstrates how the histogram can be utilized to precisely determine the segmentation line of the PCB point cloud substrate and weld connections.

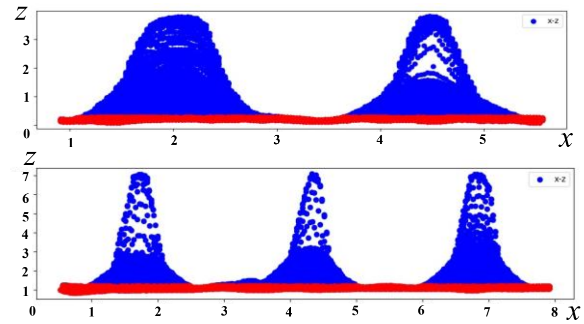

Fig 5 Segmentation line split PCB point cloud schematic

The segmentation line may be used to extract weld joints from the PCB, and the point cloud interpolation technique can be used to enhance the number of point clouds in the weld joints, therefore improving the issue of sparse weld joints on the PCB.

C. Improved Nearest Neighbor Interpolation

Considering the real industrial demands, a high number of PCBs need to be created in a restricted period for quality assessment. So, in numerous point cloud interpolation techniques, this research chooses the NN interpolation approach with the smallest time consumption.

In this paper, the method in section 2.2 is used to localize the weld joint part of the PCB point cloud, and then the nearest neighbor interpolation method is used to interpolate the weld joint point cloud, so as to propose the interpolation algorithm (Weld Joints Nearest Neighbor Interpolation ,WJ-NNI) ,The specific steps of the algorithm are as follows:

Input: PCB point cloud *xyz*.

Step1: Starting at the peak of the histogram, identify the Z-coordinate value z_{split} to the right where the vertical coordinate decreases to y≤0.2*peak* as a split line.

Step2: The PCB point cloud is interpolated using the NN interpolation method to obtain $xyz_{interpolate}$, and the interpolated point cloud of weld joints xyz_{weld} is obtained by the following equation.

$$xyz_{weld} = \{(x_i, y_i, z_i) \in xyz_{\text{interpolated}} \mid z_i \geq z_{split}\} \quad (1)$$

Step3: Merge the weld joint point cloud $xyz_{filtered}$ with the original PCB point cloud and eliminate the duplicate point cloud to create the new PCB point cloud xyz_{new}.

It is worth noting that the interpolated weld joints are merged with the original PCB point cloud in step (3) instead of merging with the segmented substrate point cloud. The main reason is that analyzing the segmentation line by histogram is not accurate enough, and relying only on the segmentation line to extract the substrate from the original point cloud to merge with the interpolated point cloud of weld joints may result in some critical points being incorrectly filtered out. To avoid this problem, the WJ-NNI method merges the interpolated weld joint point cloud with the original PCB point cloud to ensure that every point cloud is retained and important information is not missed.

IV. EXPERIMENTATION

A. Design Of Experiments

In order to validate the efficacy of the technique this study interpolates the PCB point cloud with NN and WJ-NNI algorithms. The WJ-NNI algorithm's efficacy is verified using the benchmark models PointNet ,PointNet++ ,PointConv and PointMLP. The model training environment and hardware setup include Intel (R) Core (TM) i9-7920X CPU @ 2.90GHz, 16GB of RAM, NVIDIA TITAN V, and PyTorch 1.2.0+cu10.0 with Python 3.7.12. The TABLE I below shows how the model parameters are configured.

TABLE I EXPERIMENTAL PARAMETER SETTING

Parameter	Value
Batch_size	4
Learning_rate	0.001
Optimizer	Adam
Decay_rate	0.0001
Npoint	20480
Step_size	20
Lr_decay	0.05

B. Experimental Results

In order to visualize the interpolation effect of the WJ-NNI algorithm, three point cloud data PCB_01, PCB_02 and PCB_03 are randomly selected from the PCB point cloud dataset to be interpolated with WJ-NNI, and the interpolation effect is shown in Fig 6 below. Where (1) shows the original PCB point cloud, (2) shows the interpolated weld joint point cloud, and (3) merges the interpolated weld joint point cloud with the original PCB point cloud. From the figure, it can be seen that the density of the weld joint point cloud in (3) is obviously higher than that of the weld joint point cloud in (1). Thus, it shows that WJ-NNI can effectively alleviate the problem of uneven distribution of PCB point clouds.

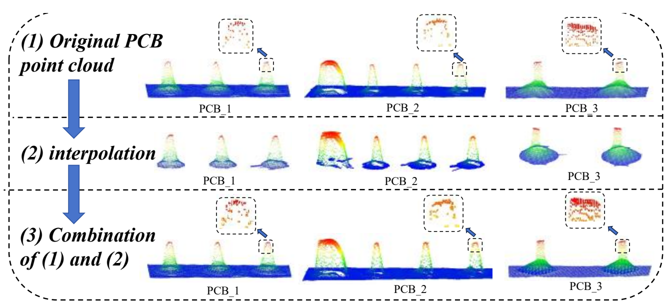

Fig 6 Schematic of WJ-NNI interpolation

Using PointNet ,PointNet++ and PointConv as baseline models, two sets of experiments were conducted for PointNet ,PointNet++ ,PointConv and PointMLP to determine whether WJ-NNI improved model segmentation performance in the welded joint segmentation experiments. The experimental results are shown in TABLE II.

TABLE II RESULTS OF EXPERIMENTS COMPARING NN AND WJ-NNI

Model	Algorithm	Overall Accuracy(%)	mIoU(%)
PointNet++	NN	90.36	83.25
	WJ-NNI	**92.71**	**86.24**
PointNet	NN	86.12	81.49
	WJ-NNI	**89.75**	**84.52**
PointConv	NN	91.89	88.06
	WJ-NNI	**93.21**	**86.99**
PointMLP	NN	82.28	84.02
	WJ-NNI	**83.92**	**86.79**

The table shows that WJ-NNI has a greater segmentation accuracy than NN on the three 3D network models, PointNet++, PointNet ,PointConv and PointMLP.

V. CONCLUSIONS

The development trend for PCB defect identification is 3D inspection. Because of the features of 3D contour imaging, the PCB point cloud that is acquired by scanning the substrate's thick weld joints sparsely has some limits when it comes to the network model that learns the weld joint information. This paper suggests the WJ-NNI algorithm, which is based on NN, to fill the sparse part of weld joints in order to solve the appeal problem. This resolves the issue of the uneven distribution of PCB point cloud, which enhances the model's capacity to learn weld joints .WJ-NNI requires more improvement in the future since, despite its low time consumption and low complexity, the WJ-NNI algorithm performs poorly when there are significant gaps in the point cloud.

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