

## IMPROVED POINTNET-BASED BINOCULAR STRUCTURED LIGHT DETECTION FOR CERAMIC BALL DEFECTS

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### Abstract

To address the low accuracy in defect detection of point clouds from binocular structured light 3D reconstruction caused by surface's high reflectivity on silicon nitride ceramic balls, this study proposes a method integrating PointNetLK point cloud registration and PointNet++ defect recognition networks. Initially, PointNet segments and removes reflective regions from the point clouds. Subsequently, an enhanced PointNetLK network performs high-precision binocular point cloud registration with missing region compensation, demonstrating two orders of magnitude improvement in registration accuracy over conventional Coherent Point Drift (CPD) + Iterative Closest Point (ICP) methods. Finally, the compensated complete point clouds are processed by an enhanced PointNet++ network incorporating a Multi-Scale Grouping (MSG) strategy for defect segmentation, effectively identifying two primary defect types (pits and scratches) with an average mIoU of 0.8565. Ablation studies confirm the critical contributions of the Set Abstraction (SA) module and MSG strategy. This approach significantly mitigates hyper-reflection interference, achieving high-precision, robust, and non-destructive quantification of ceramic ball surface defects.

**Keywords:** ceramic balls, defects detection, binocular structured light, point cloud reconstruction, PointNet.

### 1. Introduction

Silicon nitride ceramics, characterized by their lightweight nature, high hardness, exceptional strength, low friction coefficient, excellent thermal resistance, electrical insulation properties, and extraordinarily long service life, have been widely applied in the bearing systems of drive motors for new energy vehicles [1–3]. Due to the inherent brittleness of ceramic materials, coupled with complex manufacturing processes and sensitive process parameters, sporadic surface defects frequently occur on ceramic balls. Since surface quality directly impacts both bearing performance and the operational lifetime of entire systems [4], such imperfections not only substantially compromise the mechanical integrity of ceramic balls but may also trigger premature fatigue failure, severely jeopardizing system reliability and stability [5]. Consequently, implementing high-precision non-destructive inspection of finished ceramic balls is urgently required to effectively mitigate performance degradation caused by surface defects.

Currently, the traditional surface defect detection methods for ceramic balls primarily include manual visual inspection, radiographic testing, ultrasonic flaw detection, *computed tomography* (CT) technology, *etc.* [6]. For example, Deneuille *et al.* [7] early proposed an ultrasonic detection system specifically for silicon nitride ceramic balls, but the device requires the diameter of the ceramic ball to be tested to be no less than 50 mm, which has significant limitations in practical production. In addition, Industrial CT technology has high detection

accuracy and can achieve high-precision detection of structural components, making further inspection of ceramic balls possible. Chlebus *et al.* [8] applied CT detection to additive manufacturing of composite materials, using 3D modelling to analyse the unmelted metals rhenium and molybdenum in 3D printing, in order to analyse the strength of the parts. However, the high cost and huge volume of the CT equipment limits its widespread application in general industrial fields. Lei *et al.* [9] introduced an error compensated CNN model that analyses variations in ultrasonic signals to locate flow-induced void defects within ceramic materials, showing promising potential for industrial application. Besides, Zhang *et al.* [10] proposed a method for surface defect detection based on fringe reflection technology. If a ceramic ball is nondefective, the image, formed by reflection on its surface, presents even fringes. The distortion of fringes designed by a reverse exact ray-tracing method occurs at the defective region of ceramic balls.

In recent years, the development of artificial intelligence and computer vision technology has gradually brought the defect detection technology combining deep learning and machine vision into people's sight, and has become an important technical means in the field of industrial defect detection [11]. In the quality inspection of ceramic balls, deep learning technology is gradually replacing traditional manual feature engineering and rule matching methods, becoming one of the main detection methods. For example, Xu *et al.* [12] proposed an improved YOLO11-based defect detection method tailored for ceramic bearing balls to address the limitations of conventional image-processing methods in detecting intricate and variable surface defects. Li *et al.* [13] put forward a multi-view surface defect detection of ceramic bearing balls integrating features enhanced by the *Gabor salient domain* (GSMF). By improving the co-attention of multi-view to prevent memory loss caused by long-distance transmission, more feature information of the ceramic balls was preserved effectively. Jiang *et al.* [14] studied a detection method for surface defects of ceramic bearing balls based on cartoon texture decomposition model to improve the detection accuracy of surface defects of ceramic bearing balls. Similarly, Yu *et al.* [15] proposed a defect detection algorithm based on the *stationary wavelet transform* (SWT) and nonlinear enhancement to improve the detection accuracy and efficiency of silicon nitride ceramic ball surface defects. However, the above research results still have not effectively solved the fatal problem of low machine learning detection accuracy caused by high reflectivity on the surface of ceramic balls. Due to the fact that surface defects on ceramic balls can be submerged in highly reflective region to some extent, it is quite difficult to guarantee the accuracy of machine vision-based detection methods.

To address this, this paper innovatively proposes a binocular structured light point cloud detection method for ceramic ball defects that integrates the PointNetLK and PointNet++ network architectures. By enabling precise segmentation of reflective regions, achieving high-accuracy registration and missing data compensation for binocular point clouds, and incorporating multi-scale feature extraction with localized perception mechanisms, the proposed method realizes refined detection of surface defects on ceramic balls, significantly enhancing the robustness and accuracy of defect identification.

## 2. Binocular Structured Light 3D Measurement for Ceramic Balls

### 2.1. 2.1. Common Defects of Ceramic Balls

Surface defects on silicon nitride ceramic balls primarily fall into four categories: pores, pits, erosions and scratches, as illustrated in Fig. 1. Among these, pits and scratches occur most frequently across all processing stages of ceramic ball production, constituting structural integrity defects. These two types of defects not only degrade surface smoothness through wear but also act as initiation sites for crack propagation. Moreover, they severely interfere with

optical inspection processes, substantially compromising the accuracy of defect recognition. Consequently, this study specifically focuses on developing high-precision non-destructive testing methods tailored to detect pit and scratch defects.

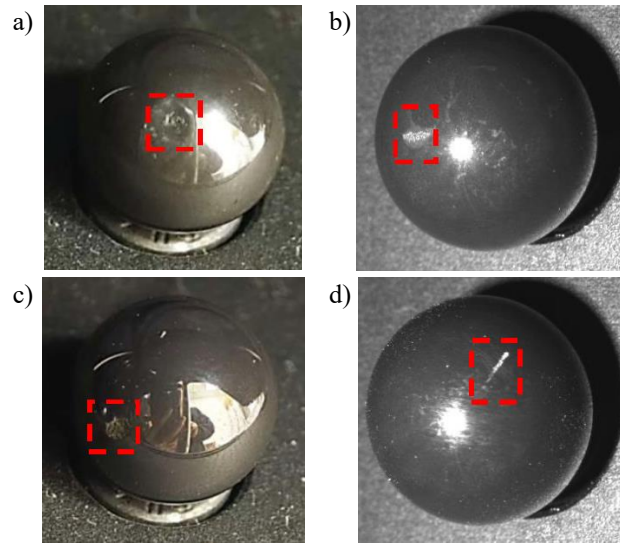


Fig. 1. Surface defects of silicon nitride ceramic balls: a) pore, b) pit, c) erosion and d) scratch.

## 2.2. Binocular Structured Light Point Cloud Reconstruction

Figure 2 illustrates a schematic diagram of a binocular structured light 3D measurement system for ceramic balls. Firstly, a structured light encoding pattern is projected onto the surface of the ceramic ball by a projector. This pattern is modulated by the surface morphology of ceramic balls and contains their three-dimensional information. Subsequently, the dual-camera captures the modulated pattern and processes it through corresponding decoding algorithms to accurately calculate the spatial information of the ceramic ball's surface points. Finally, by combining the structural light decoding and encoding algorithms such as binocular calibration [16], phase unwrapping [17], and stereo vision matching [18], 3D reconstruction of the surface morphology of the ceramic balls can be achieved.

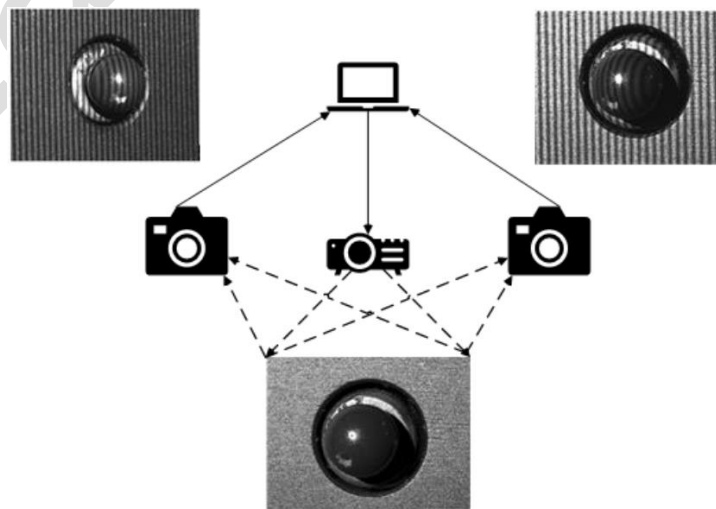


Fig. 2. Schematic diagram of binocular structured light system.

Fig. 3 shows the reconstructed contour point cloud of the ceramic ball's surface. It is not difficult to observe that the highly reflective areas on the surface of ceramic balls can lead to a certain degree of loss in the three-dimensional reconstructed point cloud data obtained from epipolar correction. Therefore, it is absolutely necessary to use point cloud post-processing technology to achieve complete and accurate reconstruction of ceramic ball point clouds, accurately locate and eliminate high reflective areas, and then use the compensated complete point cloud for subsequent detection to minimize reflective interference and ensure that defect features are presented in a realistic and detailed manner.

There are numerous advanced point cloud processing models, such as PointNet [19], PointTransformers [20], TEASER++ [21], *etc.* The first two make sense of point clouds, while the last one brings the understood point clouds into alignment. Among these point cloud models, PointNet is a pioneer and robust deep learning network used for processing 3D point cloud data. Its core structure includes an input layer, a feature extraction layer, and a fully connected layer, which achieves robust processing of point cloud disorder through max pooling. Although PointTransformers and TEASER++ are the current performance leaders, PointNet possesses the obvious advantages of effectiveness, computer efficiency, and architectural simplicity for segmentation tasks. Therefore, we are herein about to utilize the PointNet model to process the point cloud of the ceramic ball reconstructed by binocular structured light system. A detailed flowchart to illustrate the subsequent individual stages of data processing and analysis is depicted in Fig. 4.

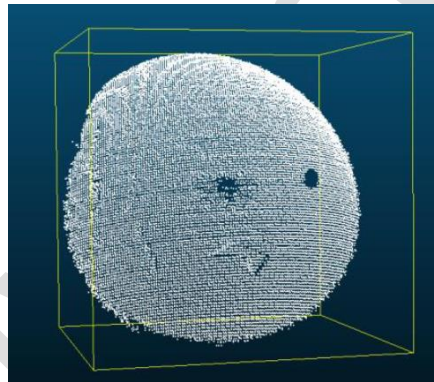


Fig. 3. 3D reconstruction points cloud of ceramic balls.

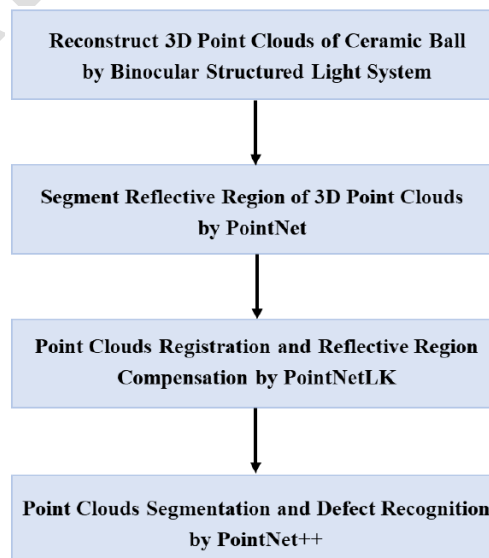


Fig. 4. Flowchart of the point clouds processing and analysis.

### 3. Ceramic Ball Binocular Point Cloud Registration and Reflection Compensation

#### 3.1. PointNet and Reflective Region Segmentation

The PointNet network architecture is depicted in Fig. 5. It employs shared *Multilayer Perceptrons* (MLPs) to perform point-wise feature extraction, subsequently aggregating individual point features into a global descriptor via max pooling, thereby enabling effective representation of overall shape and structure [22]. To mitigate variations caused by rotation and translation, the network incorporates a T-Net submodule that aligns input point clouds, ensuring the extracted features exhibit both rotation and translation invariance.

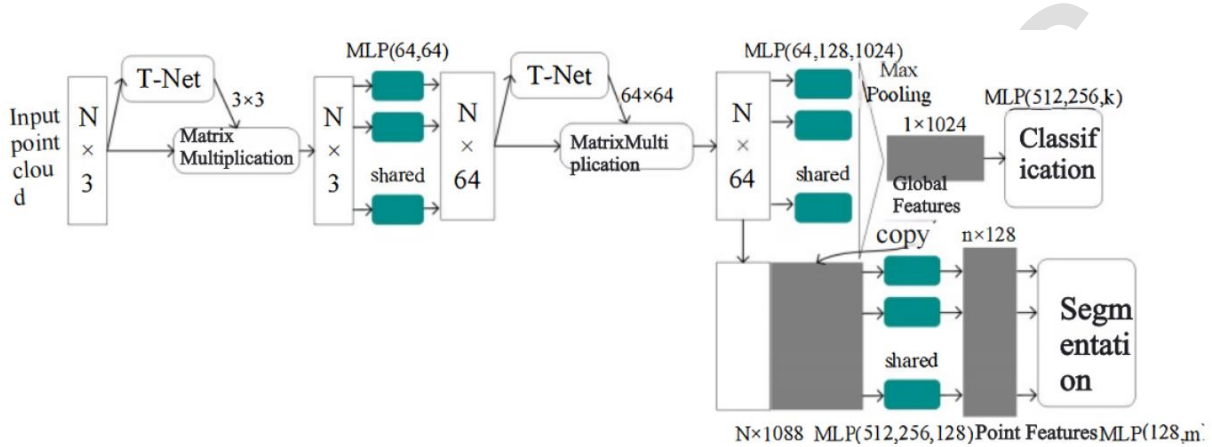


Fig. 5. PointNet network architecture.

Experiments were conducted using a self-constructed 3D reconstructed point cloud dataset of ceramic balls, encompassing both original samples and augmented samples subjected to random rigid transformations, resulting in a dataset consisting of 304 samples. The PointNet network architecture was employed for segmenting specular reflection regions within the point clouds, with experimental results detailed in Table 1.

Table 1 Experimental results of reflective region segmentation for ceramic balls.

Evaluation metrics	Reflection region segmentation	ShapeNet
Accuracy/%	93.60	83.70
mIoU/%	91.13	80.41

Experimental validation reveals that the model can achieve an accuracy rate of 93.60% and a mean Intersection over Union (mIoU) of 91.13% in segmenting specular reflection regions of the ceramic ball point clouds. As well known, ShapeNet is a widely used 3D point cloud dataset, commonly used as a sanity check. As a result, similar experiments on ShapeNet have shown that PointNet model performs robustly and has strong robustness in most segmentation tasks. The results shown in Table 1 fully demonstrate that the PointNet model used for ceramic balls' point cloud segmentation has an effective migration capability for our specific industrial scenario, *i.e.* highly reflective region segmentation.

These results demonstrate the model's high precision in segmenting specular regions. This performance advantage primarily stems from the network's enhanced capability to capture surface curvature features. To visually illustrate the segmentation effectiveness, the results are visualized in Fig. 6, where the blue point cloud represents the predicted ceramic ball surface,

and the red point cloud denotes the identified specular regions. In subsequent processing, removing the red point cloud enables the generation of a reflection-free point cloud dataset.

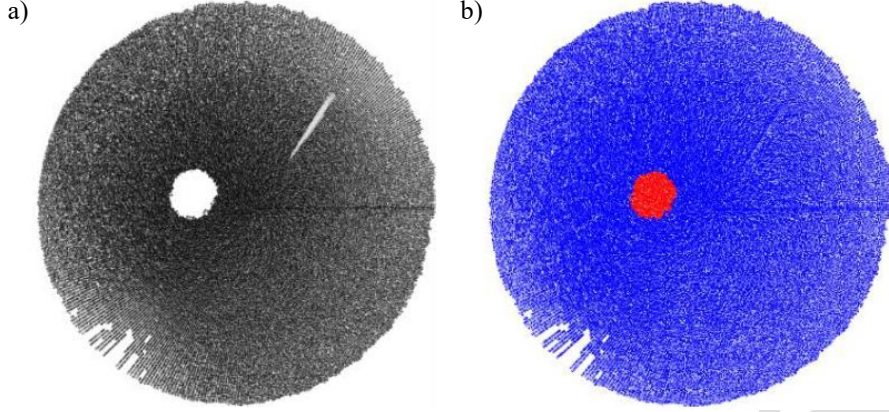


Fig. 6. Reflection region segmentation in ceramic ball point cloud: a) original point cloud, b) reflection region segmentation.

### 3.2. PointNetLK and Point Cloud Registration

PointNetLK is an innovative method for 3D point cloud registration that integrates deep learning with traditional optimization frameworks [23, 24]. By combining the feature extraction capabilities of PointNet and the optimization mechanisms of the *Lucas-Kanade* (LK) algorithm, it addresses the challenges inherent in point cloud alignment. The network architecture of PointNetLK is illustrated in Fig. 7.

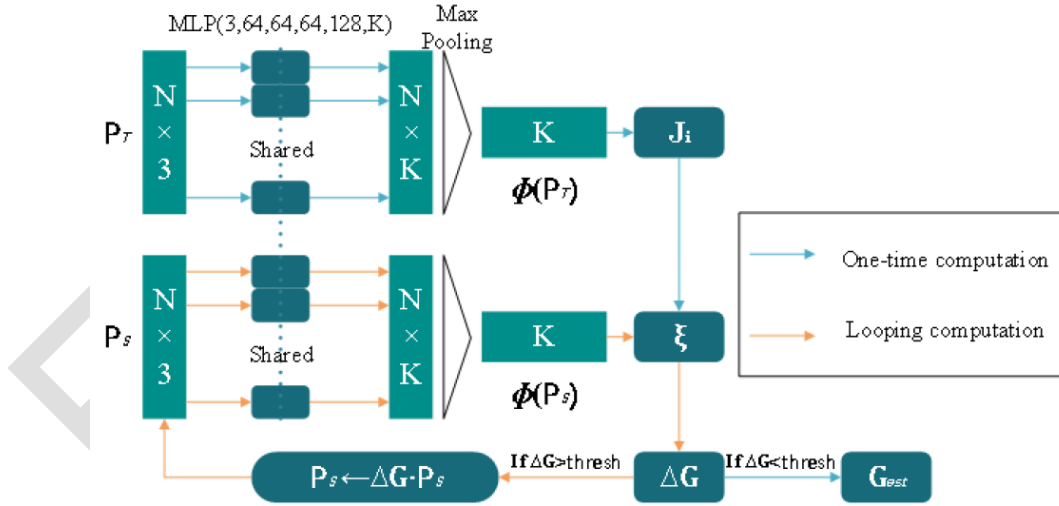


Fig. 7. PointNetLK network architecture.

Employing the *Inverse Compositional* (IC) formulation to refine the LK algorithm tackles its fundamental limitation, where conventional LK necessitates recomputing the Jacobian matrix for the transformed source point cloud at every iteration. The crux of the IC approach resides in swapping the operational roles between the template and source point clouds: within each iterative step, an incremental transformation update is initially imposed on the template point cloud, subsequently applying the inverse of this incremental transformation to the source point cloud. Defining the Jacobian matrix:

$$J = \frac{\partial[\phi(G^{-1} \cdot P_T)]}{\partial \xi} \quad (1)$$

By implementing this approach, the Jacobian matrix is computed for the template point cloud rather than the source, and this computation is executed only once prior to optimization initiation, eliminating the need for iterative updates. The Jacobian columns are approximated using finite-difference gradients within a stochastic gradient framework:

$$J_i = \frac{\phi(\exp(-t_i T_i) \cdot P_T) - \phi(P_T)}{t_i} \quad (2)$$

Where  $t_i$  represents the infinitesimal perturbations of the  $\xi$  twist parameters. The twist parameters can then be computed as  $\xi$ :

$$\xi = J^+ [\phi(P_S) - \phi(P_T)] \quad (3)$$

Where  $J^+$  denotes the Moore–Penrose pseudoinverse of the Jacobian matrix. The entire iterative algorithm computes the twist parameters using the aforementioned equation  $\xi$  generating an  $\Delta G$  incremental update for the source point cloud at each iteration  $P_S$ . When the  $\Delta G$  incremental update falls below a predefined threshold, the iterative optimization terminates. The final transformation estimate  $G_{est}$  is obtained by accumulating all incremental updates computed throughout the  $\Delta G$  iteration loop:

$$G_{est} = \Delta G_n \cdot \dots \cdot \Delta G_1 \cdot \Delta G_0 \quad (4)$$

During network training, the loss function is defined as the following Frobenius norm:

$$Loss = \|(G_{est})^{-1} \cdot G_{gt} - I_4\|_F \quad (5)$$

Where  $G_{gt}$  as the true transformation matrix  $I_4$  is the  $4 \times 4$  identity matrix. This approach exhibits superior computational efficiency, as it eliminates the necessity for matrix logarithm operations during the training phase. Following the completion of specular region segmentation, the dual-viewpoint point cloud data, with reflection components removed, is fed into the PointNetLK network for registration. To benchmark performance, a conventional *Coherent Point Drift* (CPD) + *Iterative Closest Point* (ICP) registration algorithm is employed for comparative analysis. In the domain of 3D point cloud registration, *Root Mean Square Error* (RMSE) serves as the principal evaluation metric.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n \|s_i - t_i\|_2^2}{n}} \quad (6)$$

Where  $n$  is the number of corresponding point pairs between two different coarse registered point clouds obtained from binocular structured light system, and  $s_i$  and  $t_i$  are the corresponding points belong to the source and target point clouds respectively. A smaller RMSE value indicates lower registration error and higher registration accuracy. The experimental results comparing the two registration methods are presented in Table 2.

Table 2 Comparison of two different point cloud registration algorithms.

Evaluation metric	PointNetLK	CPD+ICP
RMSE/mm	0.004730	0.1544

As demonstrated in the table above, PointNetLK based on deep learning exhibits groundbreaking advantages in the binocular point cloud registration task for ceramic balls. Its registration accuracy shows a significant improvement over the *traditional method* (CPD+ICP),

with the RMSE reduced by two orders of magnitude, achieving micrometre-level precision. The comparative registration results are illustrated in Fig. 8. In Fig. 8a, the initial state of dual-viewpoint clouds is displayed, where the blue points represent the target point cloud and the red points denote the source point cloud. Figures 8b and 8c respectively show the registration outcomes of PointNetLK and CPD+ICP. Notably, after PointNetLK registration, the alignment between the source and target point clouds becomes markedly tighter.

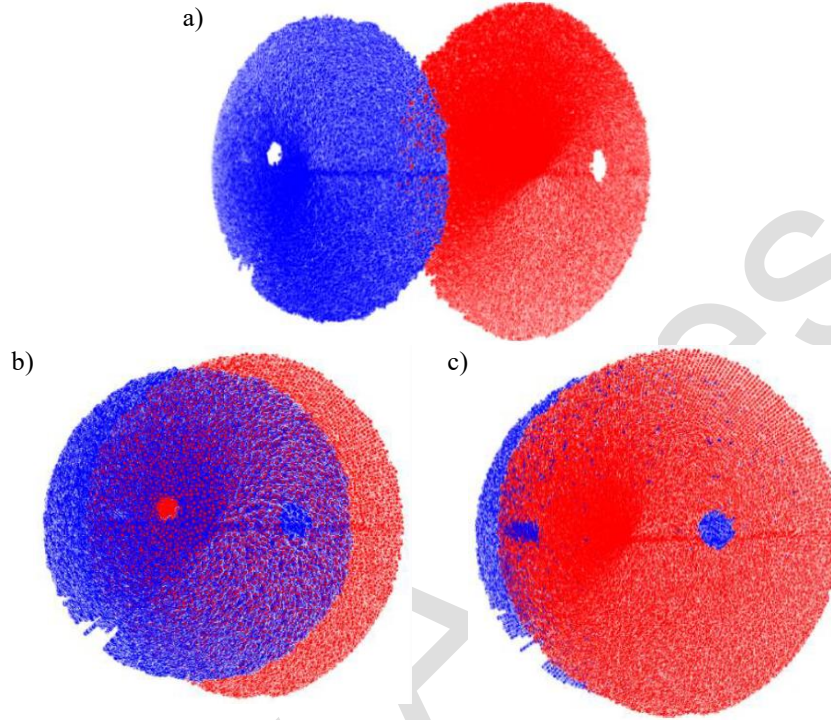


Fig. 8. Comparison of point cloud registration effects between PointNetLK and CPD+ICP: a) initial point clouds, b) PointNetLK registration effect and c) CPD+ICP registration effect.

## 4. Ceramic Balls Binocular Point Cloud Defect Detection

### 4.1. PointNet++ Network

To address the limitations of PointNet in local feature modelling and density adaptability, PointNet++ implements multiple key improvements in both network architecture and training mechanisms [25, 26]. The enhanced network architecture for the PointNet++ segmentation task is illustrated in Fig. 9.

In Fig. 9,  $N$ ,  $N_1$ ,  $N_2$  are the number of points in the point set, and  $N > N_1 > N_2$ ,  $d$  is the coordinate dimensions of points,  $c$  denotes the dimensions of other point features,  $K$  indicates the size of grouped point sets, and  $k$  expresses the number of segmentation classes. First, PointNet++ employs a hierarchical "sampling–grouping–feature extraction" set abstraction (SA) framework, recursively delving into geometric information across diverse spatial scales within point clouds. Through progressive downsampling and localized encoding at successive layers, the model significantly enhances its sensitivity to microscopic details (such as edges and textures) while preserving global shape information, thereby providing richer and more stable multi-scale feature representations. Second, PointNet++ introduces a *Multi-Scale Grouping* (MSG) strategy within each set abstraction module. By parallelizing neighborhoods with various radius, it simultaneously captures both large-scale contextual features and fine-grained local details.

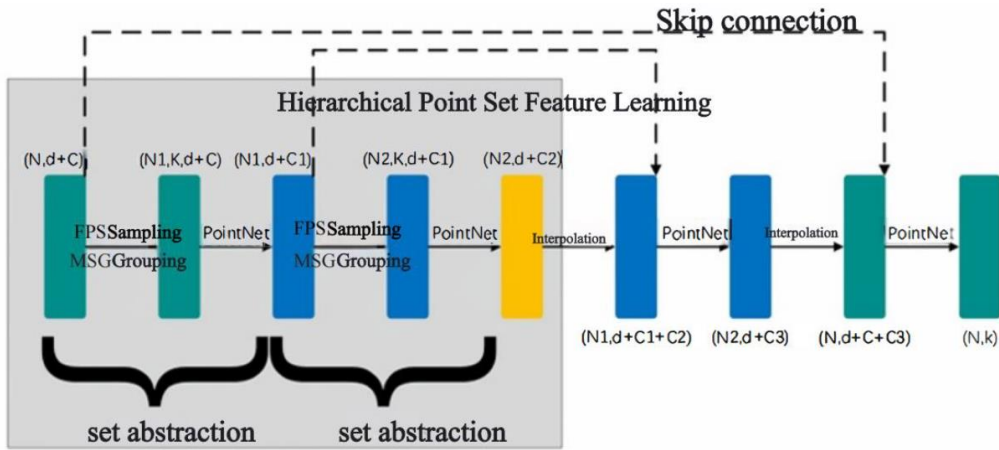


Fig. 9. Network architecture of PointNet++ for segmentation task.

After undergoing multiple optimizations, the PointNet++ network generates a set of score weights corresponding to each segmentation class for every point. Finally, by comparing these weights and selecting the maximum value, the category assignment for each point can be accurately determined. This workflow demonstrates greater stability and precision when processing point clouds segmentation scenarios characterized by significant density variations and complex geometric structures.

#### 4.2. Defect Segmentation Experiment

The experiment is based on the PyTorch deep learning framework and utilizes an RTX 4060 graphics card for model training. The specific configuration of the experimental environment is detailed in Table 3.

Table 3 Experimental environment.

Environment name	
Operating system	Ubuntu 22.04.5
GPU	RTX4060
CPU	13th Gen Intel(R) Core(TM) i9-13900HX 2.20 GHz
RAM	32.0GB
Deep learning framework	PyTorch(2.1.1)
Interpreter	Python(3.11)
CUDAVersion	CUDA(12.1)

A total of 404 point clouds of ceramic balls were collected in this experiment, encompassing two defect types: pits and scratches. The raw point clouds initially underwent butterfly subdivision upsampling. Subsequently, the processed data was fed into the PointNetLK network to eliminate reflection regions while completing viewpoint registration and compensation. Following this pipeline, 202 valid samples were retained, comprising 105 pit-defected ceramic ball point clouds and 97 scratch-defected counterparts, all manually annotated for defects. Finally, the dataset was split according to a 7:2:1 ratio into training, testing, and validation sets. The distribution details of ceramic ball samples are summarized in Table 4.

Table 4 Sample division results of silicon nitride ceramic balls.

Defect type	Number of points	Proportion	Label
Pit	79275	0.5%	0
Scratch	44814	0.8%	1
Spherical surface	18055911	98.7%	2

During the training of PointNet++, we employed a batch size of 16 and selected the Adam optimizer with an initial learning rate set to 0.001. The learning rate was adjusted using a decay rate of 0.0001, triggering a reduction every 20 epochs. The input point clouds were sampled to 2048 points, and the entire training process spanned 250 epochs to ensure comprehensive learning of complex spatial features. The evolution of Mean Intersection over Union (mIoU) metrics across defect categories, spherical surfaces, and their average values throughout the epochs is illustrated in Fig. 10. The optimal performance results of the PointNet++ model are presented in Table 5.

Table 5 Optimal performance of PointNet++ for segmentation task.

Evaluation metric	Scratch	Pit	Spherical surface	Average
mIoU	0.8113	0.8755	0.9070	0.8565
F1	0.8275	0.8848	0.9142	0.8663

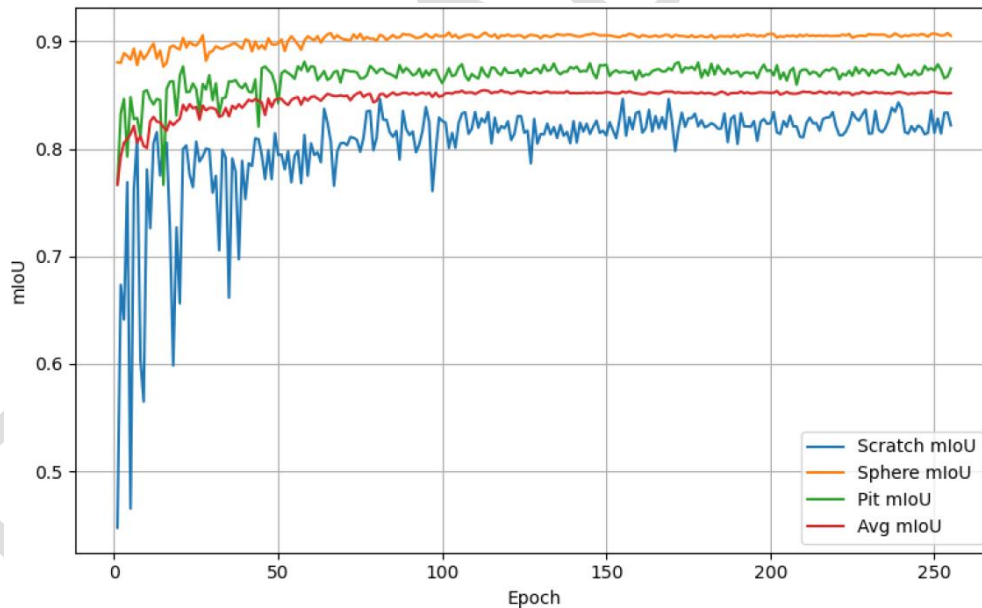


Fig. 10. Visualization analysis of defect segmentation experimental data.

From the curves in Fig. 10, it is evident that during the initial training phase, the mIoU values for all categories exhibited significant fluctuations. As the number of iterations increased, these metrics rapidly rose and stabilized after approximately 100 epochs: The regular, well-sampled spherical surfaces (orange) converged first, with mIoU increasing from 0.8805 to 0.9070; followed by medium-sized pits (green), which ultimately stabilized at 0.8755; while linear, thin-boundary scratches (blue) started lowest (0.45) but surged quickly within the first 30 epochs to reach 0.80, maintaining slight oscillations thereafter. The overall average mIoU (red)

consistently improved from 0.7667 to 0.8565, demonstrating that the model achieved a balanced and efficient segmentation capability for both defect types.

Figure 11 and Fig. 12 respectively illustrate the visual detection and recognition results of the improved PointNet++ network corresponding to two pit defects and scratch defects for silicon nitride ceramic balls. In Fig. 11 and Fig. 12, red, green, and blue point clouds are used to mark pit defects, scratch defects, and normal reflection surface regions, respectively, forming an intuitive spatial distribution map of defects. The experiments validate the feasibility and effectiveness of the improved PointNet++ network in detecting various surface defects on silicon nitride ceramic balls.

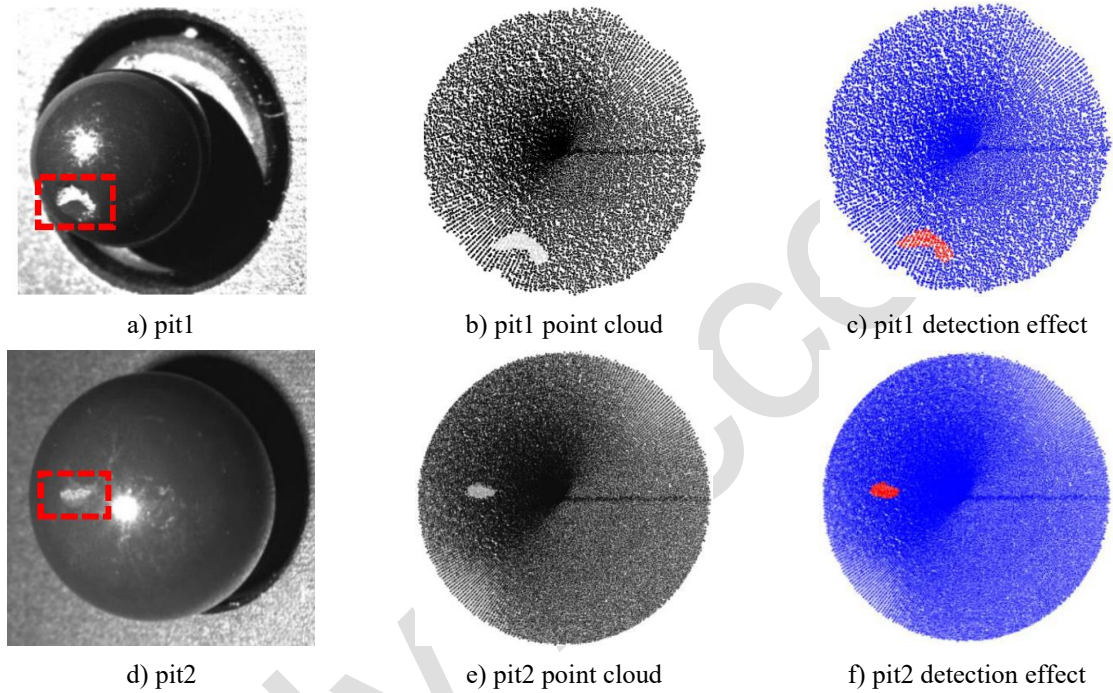


Fig. 11. Ceramic ball pit defects detection results.

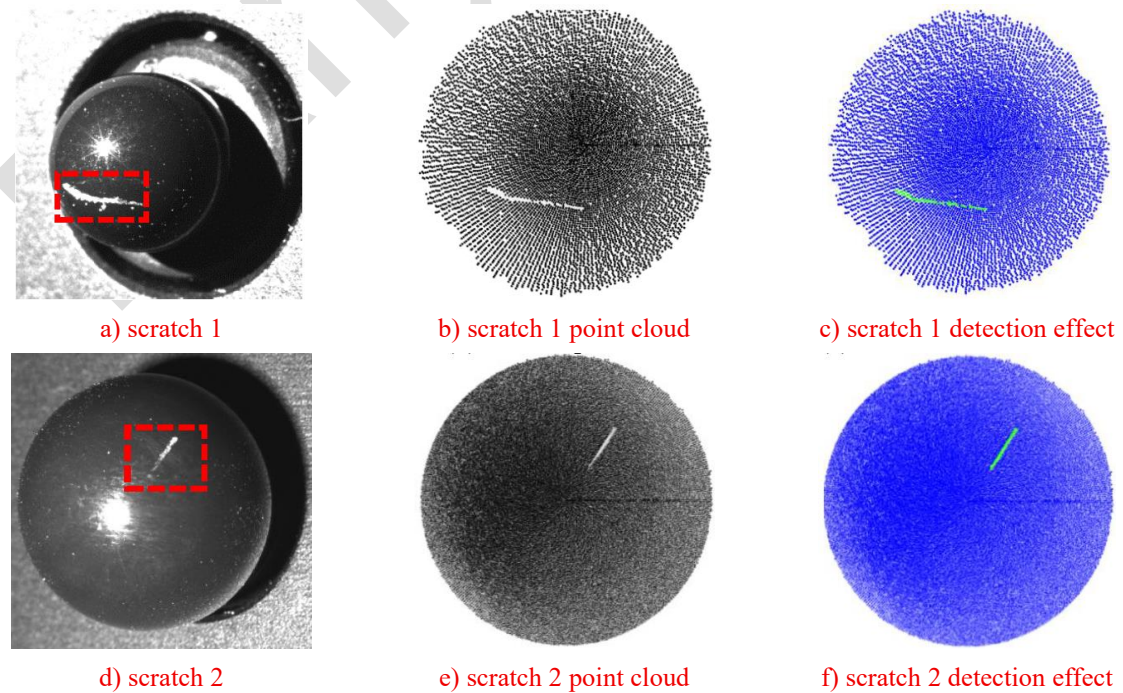


Fig. 12. Ceramic ball scratch defects detection results.

### 4.3. Ablation Study Analysis

An ablation study was conducted on two critical improvements of the PointNet++ model, SA and MSG, to evaluate their performance enhancement in silicon nitride ceramic ball surface defect segmentation tasks. The SA module enables hierarchical sampling and localized feature extraction, allowing the model to effectively capture local geometric structures within point clouds. Compared to the original PointNet model, incorporating the SA module resulted in a significant improvement in the mIoU metric for segmentation tasks, demonstrating the crucial role of local features in identifying surface defects. Furthermore, optimizing *Single-Scale Grouping* (SSG) to the MSG strategy involved employing multiple search radii around each sampled point to extract multi-scale local features. This approach enhanced the model's robustness to defects of varying sizes and shapes. Experimental results showed that combining the MSG strategy led to further improvements in the mIoU metric. The experimental results are presented in Table 6.

Table 6 Results of ablation study.

Model	+SA	+MSG	Avg mIoU	F1
PointNet			0.7887	0.8020
PointNet++(SSG)	✓		0.8303	0.8438
PointNet++(MSG)	✓	✓	0.8565	0.8663

Experiments demonstrate that the hierarchical feature learning and MSG strategy based on the improved PointNet++ significantly enhance the segmentation accuracy and robustness for detecting small defects, such as pits and scratches, on the surface of silicon nitride ceramic balls, exhibiting distinct advantages over the traditional PointNet method.

In summary, both PointNetLK and PointNet++ we used essentially utilize depth features as state feedback to actively estimate and compensate for the uncertainty of point cloud loss and noise caused by reflection and occlusion through iterative optimization (feature rollback). This data-driven compensation mechanism is similar to the model reference adaptive control strategy in control theory in the core logic of estimation compensation.

The main novelty lies in innovatively transferring and implementing this idea from the traditional field of dynamic system control to static point cloud data processing for visual tasks. We did not explicitly model system dynamics, but implicitly learned how to achieve robust alignment in the feature space through deep networks to compensate for uncertainty at the data level. This provides a new approach to dealing with uncertainty issues in complex visual perception that echoes control theory but has a different implementation path.

## 5. Conclusions

This paper addresses the challenge of high reflection interference encountered when applying binocular structured light for surface defect detection on silicon nitride ceramic balls. It proposes a novel solution integrating a PointNetLK point cloud registration network with an improved PointNet++ point cloud segmentation network, enabling high-precision and non-destructive testing of typical defects such as pits and scratches on ceramic ball surfaces.

The proposed method achieved an accuracy rate of 93.6% on a self-developed ceramic ball point cloud dataset, effectively localizing and eliminating highly reflective regions. PointNetLK accomplished micrometeor level registration accuracy (RMSE = 0.0047mm), demonstrating a two-order-of-magnitude enhancement compared to the traditional CPD+ICP

method and significantly optimizing reflection compensation. By incorporating a MSG strategy, PointNet++ achieved average mIoU of 0.8565 for pit segmentation (mIoU = 0.8755) and scratch segmentation (mIoU = 0.8113), with ablation studies confirming significant contributions from both the SA and MSG modules, yielding an 8.78% improvement over conventional PointNet.

This method provides a new paradigm for detecting surface defects on high reflective ceramic balls, and its robustness and accuracy are sufficient to meet the requirements of industrial batch testing. Future work will focus on deep integration with adaptive robot systems to achieve closed-loop detection decision operations, which is of great significance for improving the automation and intelligence level of ceramic ball surface defect detection.

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