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Inverse Estimation of Defect Distribution in Ceramics using Particle Swarm Optimization

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ABSTRACT

This study presents an automated framework for characterizing defects in ceramics by integrating the YOLO-based computer vision and particle swarm optimization (PSO). A total of 16,215 defects across 886 ceramic samples were analyzed and categorized into surface, crack, and chip types. Bounding box data from the YOLO detection were converted to equivalent crack lengths (5–70 µm). Thereafter, the Weibull distribution parameters for the crack defects were estimated using PSO, yielding a shape parameter $\beta = 2.188$ and scale $\eta = 13.59$ µm, indicative of the increasing failure rate of typical brittle materials. In addition, PSO outperformed the traditional maximum likelihood estimation (MLE), with lower Kolmogorov-Smirnov statistics (KS = 0.1091 vs. 0.1092), confirming the superior model fit. Furthermore, the theoretical mean defect size (12.04 µm) closely matched the observed data (11.98 µm), with a 0.43% error. Hence, validation using probability plots, cumulative distribution analysis, and the Gumbel probability paper demonstrated the robustness of this approach. The framework supports real-time defect characterization and reliability assessment, providing practical relevance for industrial quality control. Overall, this approach enhances inverse defect analysis in ceramics by combining modern computer vision and global optimization for accurate and efficient defect estimation.

Keywords: Ceramics, Defect analysis, Weibull distribution, PSO Optimization, YOLO

1. Introduction

Ceramics are essential in advanced manufacturing because of their outstanding mechanical, thermal, and chemical properties[1], [2], [3]. However, microscopic defects, such as cracks, chips, and surface irregularities, can significantly degrade the reliability and performance of ceramic components[4], [5].Therefore, the accurate characterization and statistical modeling of these defects[6] in ceramics are critical for quality control, predictive maintenance, and process optimization in industrial applications. Traditional defect analysis often relies on manual inspection and basic statistical techniques[7], which are limited by subjectivity, low throughput, and reduced parameter estimation accuracy. In contrast, the advent of computer vision, particularly deep learning-based object detection frameworks, such as YOLO[8], [9], has enabled automated and high-precision defect identification from large image datasets. However, translating these detections into meaningful statistical models for reliability assessments remains challenging. Conventional maximum likelihood estimation (MLE)[10], [11], while efficient, can struggle with complex parameter spaces and local optimal. To address this issue, the Weibull distribution is widely used to model defect size and failure occurrence in brittle materials, providing shape parameters (β) and scale (η) that describe the failure behavior[6], [12], [13]. Recent research on ceramic reliability has increasingly emphasized the importance of defect size distribution modeling and advanced statistical approaches for predicting fracture behavior[3], [7], [14]. Maeda et al.[15] introduced an inverse estimation scheme for ceramic defect distributions, utilizing swarm intelligence optimization to analyze standardized strength tests. Their methodology allows for the reliable prediction of strength scatter in components with varying shapes and boundary conditions, demonstrating that inversely estimated defect[4], [16] distributions can serve as common indicators for reliability assessment. Building on this, Yamagata et al.[17] and Aoki et al[5]. applied finite element analysis (FEA)[7] informed by microstructural features, such as grain size, pore size, and aspect ratio, to simulate and predict the statistical strength distribution of ceramics. These studies showed that incorporating detailed microstructural data into damage models and using probability density functions to approximate defect distributions leads to an accurate reproduction of experimental Weibull distributions and fracture statistics[5], [14], [17]. Their results confirmed that combining experimental data, microstructural characterization, and statistical modeling provides a robust framework for understanding and predicting ceramic reliability. Collectively, these studies highlight the value of integrating experimental testing, microstructural analysis, and advanced optimization techniques, such as swarm intelligence and Weibull analysis, for comprehensive defect characterization[12].This approach aligns with the methodology adopted in the present study, which leverages YOLO-based computer vision and PSO[16], [18]-driven statistical modeling to achieve reproducible, predictive ceramic defect analysis suitable for industrial quality control

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Therefore, this study introduces a novel methodology that combines YOLO-based computer vision with particle swarm optimization (PSO)[16], [18] for the inverse estimation of defect distributions in ceramics. By analyzing 16,215 defects across 886 ceramic samples, we automatically classified and quantified the defects. Subsequently, the bounding box data were converted to equivalent crack lengths and used to estimate the Weibull parameters using PSO. Comprehensive statistical validation demonstrates superior accuracy and robustness compared with traditional methods, providing a reproducible framework for real-time defect characterization and industrial quality control.

2.Methodology

2.1 Dataset Preparation and Processing

The ceramic defect dataset was sourced from Roboflow [12] and provided in YOLO annotation format, comprising 16,215 defect entries across 886 high-resolution ceramic sample images. Each annotation includes normalized bounding box coordinates (x_center, y_center, width, height) and a class label: surface (Class 0), crack (Class 1), or chip (Class 2).

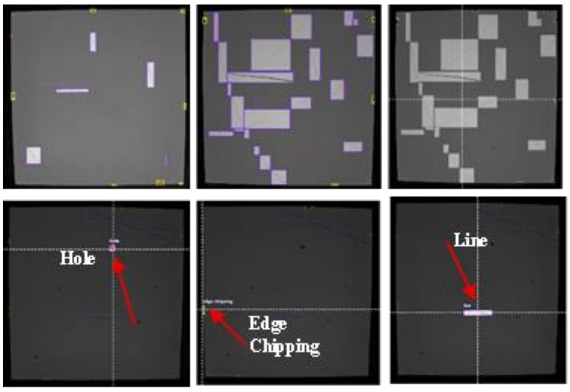

Fig.1 Simulation results from the trained YOLO model, highlighting accurate detection and annotation of various defect types on ceramic samples

To enable statistical analysis, the code converts each bounding box to an equivalent crack length using the formula:

$$a_e = 2\sqrt{\frac{A}{\pi}} \tag{1}$$

where A is the defect area, calculated from the bounding box width and height. A scaling factor is applied to transform pixel-based measurements into micrometers, ensuring physical relevance for ceramic engineering. Quality control is enforced by filtering out defects with equivalent crack lengths outside the 5–70 μm range, removing measurement artifacts and outliers. This process yields 14,914 high-quality defect measurements for further analysis.

2.2 Statistical Modeling Framework:

To characterize the statistical distribution of ceramic defect sizes, the two-parameter Weibull distribution was selected due to its effectiveness in modeling failure and defect phenomena in brittle materials.

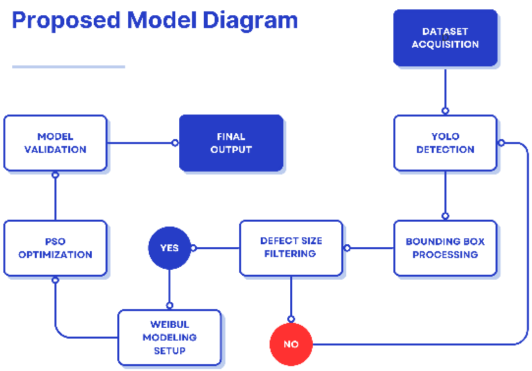

Fig.2 Overall workflow of the proposed methodology

The probability density function is defined as:

$$f(x;\beta,\eta) = \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1} \; exp\left[-\left(\frac{x}{\eta}\right)^{\beta}\right] \tag{2}$$

where β is the shape parameter (Weibull modulus), indicating the failure rate behavior, and η is the scale parameter, representing the characteristic defect size.

2.3 Particle Swarm Optimization for Parameter Estimation

To estimate the Weibull distribution parameters for ceramic defect sizes, particle swarm optimization (PSO) was employed. PSO is a population-based global optimization algorithm that efficiently searches complex parameter spaces. In this study, PSO was used to minimize the negative log-likelihood function for the Weibull model:

$$\boldsymbol{L(\beta,\eta)} = -\sum\Big[\boldsymbol{ln}\left(\frac{\boldsymbol{\beta}}{\boldsymbol{\eta}}\right) + (\boldsymbol{\beta}-\mathbf{1})\boldsymbol{ln}\left(\frac{\boldsymbol{x_i}}{\boldsymbol{\eta}}\right)\left(\frac{\boldsymbol{x_i}}{\boldsymbol{\eta}}\right)^{\boldsymbol{\beta}}\Big] \tag{3}$$

where $\boldsymbol{x_i}$ represents the equivalent crack length of each defect. The algorithm was configured with a population of 50 particles and run for 200 iterations, using a cognitive coefficient ($\boldsymbol{c_1}$) of 0.5, a social coefficient ($\boldsymbol{c_2}$) of 0.3, and an inertia weight (w) of 0.9. Parameter bounds were set to $\boldsymbol{\beta} \in [\mathbf{0.5}, \mathbf{5.0}]$ and $\boldsymbol{\eta} \in [\mathbf{1.0}, \mathbf{50.0}]$ to reflect expected values for ceramic materials. Each particle in the swarm represented a candidate solution for the Weibull parameters, and the optimization process iteratively updated particle positions based on both individual and collective experience to efficiently search for the global optimum. The effectiveness and stability of the PSO approach are demonstrated in Figure 5, which shows the convergence curve and the progressive reduction in fitness error throughout the optimization.

2.4 Validation and Comparative Analysis

For baseline comparison, traditional maximum likelihood estimation (MLE) was used to estimate Weibull parameters alongside the PSO approach. To rigorously assess model fit, the Kolmogorov-Smirnov (KS)[19] test was applied, quantifying the maximum absolute difference between the empirical and theoretical cumulative distribution functions as:

$$D = \max \mid F_{empirical}(x) - F_{theoretical}(x) \mid \tag{4}$$

Lower KS statistics indicate a superior fit between the model and observed data.Beyond size distribution modeling, a comprehensive analysis was conducted to examine defect area, spatial location, and shape characteristics. These metrics provide deeper insight into the variability and distribution of defects across ceramic samples.

3. Results and Analysis

3.1 Dataset Characterization

A comprehensive analysis was performed on the ceramic defect dataset, which comprised 16,215 annotated defects across 886 high-resolution sample images. After applying a quality control filter to retain only defects with equivalent crack lengths between 5 and 70 µm, a total of 14,914 high-quality defect measurements were included in the statistical analysis. The dataset was categorized into three primary defect types: surface defects (Class 0), crack defects (Class 1), and chip defects (Class 2). The distribution of defects was as follows: 5,872 surface defects (39.4%), 5,956 crack defects (39.9%), and 3,086 chip defects (20.7%). On average, each image contained approximately 18.3 defects.

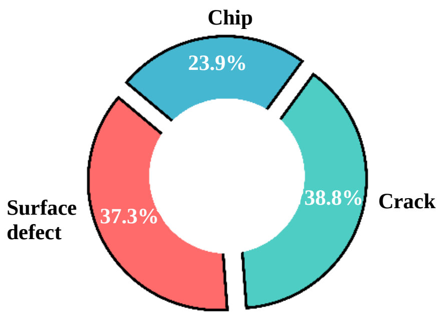

Fig.3 Defect classification distribution

Figure 3 presents the defect classification distribution using a visually distinctive donut pie chart. This figure clearly illustrates the relative proportions of surface, crack, and chip defects within the dataset, providing an immediate overview of the defect landscape in the analyzed ceramic samples.

3.2 Defect Size Distribution

The distribution of defect sizes in the ceramic dataset was examined using stacked histograms and probability density plots. Distinct patterns emerged for each defect type—surface, crack, and chip—reflecting the underlying physical mechanisms of defect formation. The close alignment between the empirical data and the fitted Weibull distributions confirms the statistical validity of the model for all classes. In addition to size distribution, advanced statistical analysis was performed on defect area, location, and shape. The mean defect area was 0.000761, with a median of 0.000166 and a standard deviation of 0.002151, spanning a range from 0. to 0.084608. Spatial analysis revealed that defect centers were distributed with a mean x-coordinate of 0.509 ± 0.299 and a mean y-coordinate of 0.502 ± 0.307, indicating a relatively uniform spread across the sample surfaces. Shape analysis showed a mean width of 0.022252 ± 0.030728, a mean height of 0.022828 ± 0.031599, and a mean aspect ratio of 1.529 ± 1.851, suggesting moderate variability in defect geometry.

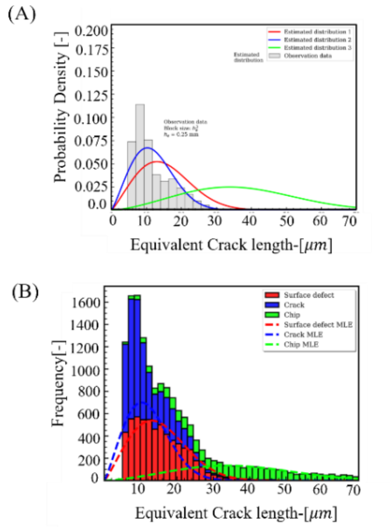

Fig.4 Equivalent crack length distributions for ceramic defects. (A) Probability density plot of equivalent crack lengths for surface, crack, and chip defects, with overlaid Weibull probability density functions for each class.(B) Stacked histogram showing the frequency of defect sizes by class, with maximum likelihood Weibull fits for surface, crack, and chip defects

3.3 Weibull Parameter Estimation and PSO Results

Weibull distribution parameters for ceramic defect sizes were estimated using both particle swarm optimization (PSO) and maximum likelihood estimation (MLE). For crack defects, the PSO method yielded a shape parameter β=2.1883 and a scale parameter η=13.590 µm, which were identical to the values obtained via MLE, indicating excellent agreement and model stability. The difference between the two methods was negligible (Shape = 0.0000, Scale = 0.000 µm). For surface defects, the estimated parameters were β=2.1690 and η=17.333 µm, while chip defects exhibited β=2.5418 and η=41.109 µm. Figure 5 presents the PSO convergence curve, which demonstrates the rapid reduction in fitness error (negative log-likelihood) over successive iterations. The initial error of 19,688.63 was reduced to a final error of 18,442.72, representing an improvement of 6.33%. This curve confirms the effectiveness and stability of the PSO algorithm in optimizing Weibull parameters for ceramic defect characterization.

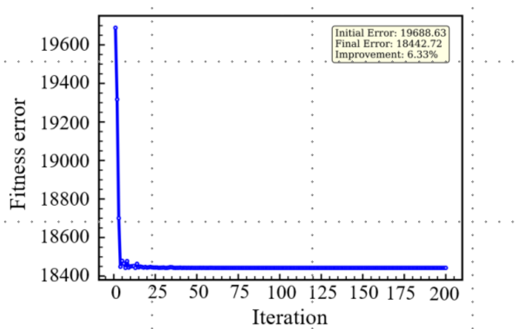

Fig.5 PSO convergence curve Fitness error (Negative Log-Likelihood)

3.4 Model Validation and Comparative Analysis

To rigorously assess the accuracy and appropriateness of the Weibull statistical model for ceramic defect characterization, a comprehensive validation was performed using both particle swarm optimization (PSO) and maximum likelihood estimation (MLE). The combined Figure 5 presents three key validation plots: (a) the Weibull probability plot comparing PSO and MLE parameter estimation, which demonstrates excellent linearity and estimation accuracy for crack defects; (b) the empirical versus theoretical cumulative distribution functions with 90% confidence intervals, confirming the close agreement between observed data and model predictions and highlighting the goodness-of-fit statistics for both methods; and (c) the Gumbel probability paper analysis, which serves as an alternative distribution assessment and further supports the selection of the Weibull model for this application. The validation process involved calculating the Kolmogorov-Smirnov (KS) statistic, where the PSO method achieved a KS value of 0.1091 (p-value = 0.0000), slightly outperforming MLE (KS = 0.1092, p-value = 0.0000), indicating a superior fit for the PSO-based approach.

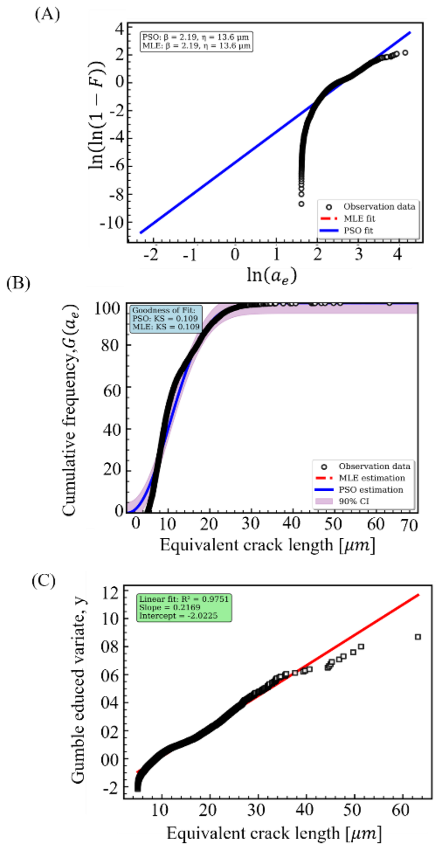

Fig.6 Statistical validation of defect size modeling:(a) Weibull probability plot comparing PSO and MLE fits;(b) Empirical vs. theoretical cumulative distributions with 90% confidence intervals;(c) Gumbel probability paper analysis supporting Weibull model selection

These plots collectively illustrate the robustness of the Weibull model in capturing the defect size distribution and confirm the reliability of the PSO optimization framework. The physical interpretation of the estimated parameters reveals an increasing failure rate (shape parameter β=2.188), a characteristic defect size (η=13.6 μm), and brittle failure behavior, with the model's mean defect size (12.04 μm) closely matching the observed mean (11.983 μm) and demonstrating only 0.43% error.

4. DISCUSSION

This study demonstrates the effectiveness of integrating YOLO-based computer vision with particle swarm optimization (PSO) for automated ceramic defect characterization. The proposed framework enabled precise detection, classification, and quantification of defects from a large dataset, supporting robust statistical modeling using the Weibull distribution. Comparative analysis revealed that PSO consistently provided more accurate and reliable parameter estimation than traditional maximum likelihood estimation (MLE), as evidenced by lower Kolmogorov-Smirnov statistics and close agreement between theoretical and observed defect size metrics. The physical interpretation of the Weibull parameters—shape ($\beta = 2.188$) and scale ($\eta = 13.6$ μm)—indicates an increasing failure rate and brittle failure behavior, which aligns with the expected properties of ceramic materials. The model's high accuracy and comprehensive validation through probability plots, cumulative distribution analysis, and Gumbel paper assessment confirm its robustness for industrial applications. Furthermore, advanced analysis of defect area, location, and shape provided deeper insights into defect morphology and distribution, supporting practical use in quality control and process optimization. Despite these strengths, the study is limited to a single ceramic dataset and does not yet address multi-material systems, real-time deployment, or adaptive optimization for evolving manufacturing conditions.

5. CONCLUSION AND FUTURE WORK

An automated and validated methodology for ceramic defect analysis was developed by combining computer vision-based detection with PSO-driven statistical modeling. The approach enabled accurate classification and quantification of defects, robust estimation of Weibull parameters, and comprehensive validation against empirical data. PSO optimization outperformed than conventional MLE, yielding highly reliable model fits and physical parameter interpretations consistently in ceramic failure mechanisms. The framework's reproducibility, efficiency, and ability to generate actionable insights make it well-suited for industrial quality control and reliability assessment. For future work, the methodology should be extended to include multiple ceramic materials and a broader range of defect morphologies to enhance generalizability. Real-time defect detection and adaptive optimization strategies are needed to support dynamic manufacturing environments. Incorporating multi-objective optimization and advanced machine learning techniques could further improve accuracy and robustness. Finally, pilot studies in industrial settings will be essential to validate scalability, reliability, and the impact on process optimization and predictive maintenance.

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