ITM Web of Conferences **80**, 03007 (2025) https://doi.org/10.1051/itmconf/20258003007
ACAAI 2025

Development of an Online Defect Detection System for Additive Manufacturing Based on Multi-Sensor Fusion

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Abstract. Additive Manufacturing (AM), especially metal Selective Laser Melting (SLM), is essential for high-end industries like aerospace (e.g., turbine blades) and medical implants (e.g., hip implants), but in-situ defect detection remains a key bottleneck limiting its industrialization. Existing single-sensor systems fail to cover surface-subsurface-internal defects comprehensively, while traditional multi-sensor fusion suffers from information loss and poor real-time performance. This study develops an online system integrating visible light, infrared, and ultrasonic sensors, proposing a cross-modal attention-enhanced NSCT-PCNN fusion algorithm to optimize multi-modal feature fusion and an improved YOLOv3 (with an additional small-scale branch and CIoU loss) to boost detection precision. Experiments on the EOS M290 machine using Ti-6Al-4V material show the system achieves 95.8% mAP, 92.3% small defect detection rate, and 21.5 fps speed. Closed-loop control based on the system reduces the defect rate of components from 18.5% to 5.2%, and tensile strength increases by 12.3%. Future work will upgrade ultrasonic hardware and validate the system's adaptability to multi-material AM processes.

1 Introduction

Additive Manufacturing (AM), particularly metal SLM, enables complex component fabrication for aerospace (e.g., turbine blades) and medical (e.g., hip implants) sectors [1]. However, SLM's complex physical-chemical processes cause defects (pores: 5–50 μm, interlayer cracks: 10–200 μm, lack of fusion: >0.1 mm²), which reduce Ti-6Al-4V fatigue life by 30%–50% [2]. Traditional offline detection (CT, metallography) is destructive and non-real-time [3], while single-sensor systems have limitations: visible light detects surface spatter (92.3% accuracy) but not subsurface pores [4]; infrared infers cracks (88.1% recall) but is noisy [5]; X-ray has 5 μm resolution but is costly and slow [6, 7]. Multi-sensor fusion addresses coverage issues, yet data-level fusion is computationally heavy [8], decision-level underuses cross-modal links [9], and feature-level fusion (e.g., NSCT) uses fixed rules, losing details [10]. Transformer-based fusion (94.5% mAP) is too slow (8 fps) for SLM (scanning speed >10 mm/s) [11]. This study designs a synchronous multi-sensor system, develops an

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attention-enhanced fusion algorithm, and optimizes YOLOv3 for real-time small defect detection (>20 fps, >90% rate).

2 Defect analysis in am and multi-sensor fusion principles

2.1 Defect types and formation mechanisms in SLM

2.1.1 Defect characteristics

Experiments were conducted using Ti-6Al-4V powder (particle size 15–53 μm) on an EOS M290 SLM machine. Table 1 summarizes the characteristics of typical defects:

Table 1. Characteristics of typical SLM defects

Defect Type	Size Range	Location	Harm
Pore	5–50 μm	Internal	Reduces fatigue strength
Interlayer crack	10–200 μm	Internal	Causes component fracture
Lack of fusion	>0.1 mm²	Surface/Internal	Degrades dimensional accuracy
Spatter	50–200 μm	Surface	Increases surface roughness

2.1.2 Formation mechanisms

Pores form when incomplete powder melting (caused by low laser power <180 W) traps gas bubbles in the molten pool;

Interlayer cracks occur because rapid cooling rate differences ($\Delta T > 500$ °C/s) from high scanning speed (>1200 mm/s) generate thermal stress exceeding the material's yield strength;

Lack of fusion results from insufficient powder bed density (<60%), which reduces the bonding force between adjacent layers.

2.2 Multi-sensor fusion fundamentals

2.2.1 Fusion layers comparison

Multi-sensor fusion is classified into three layers based on information processing stages (Table 2):

Table 2. Comparison of multi-sensor fusion layers

Fusion Layer	Processing Object	Advantages	Disadvantages
Data-level	Raw pixels/signals	Minimal information loss	High computational cost
Feature-level	Extracted feature vectors	Balances accuracy and speed	Relies on feature quality

Decision-level	Single-model results	Strong anti-interference	Low information utilization

Feature-level fusion is selected in this study for its suitability for dynamic AM processes, as it retains critical defect features while reducing computational complexity [12].

2.2.2 Limitations of traditional fusion methods

NSCT fusion has fixed coefficient fusion rules that fail to distinguish between defect features and noise, leading to missed detection of subtle defects (e.g., <20 μm pores);

PCNN fusion requires manually set linking strength parameters (typically 0.5–1.0), which results in poor adaptability to complex molten pool backgrounds and increases false detection rates [13].

3 System design

3.1 Overall system architecture

The system consists of hardware (sensor array, data acquisition card, industrial computer) and software (data preprocessing, fusion recognition, visualization control) modules.

3.1.1 Hardware configuration

Sensor parameters and deployment are optimized for EOS M290 SLM machine specifications (Table 3):

Table 3. Sensor parameters and acquisition targets

Sensor Type	Model	Resolution	Frame Rate	Acquisition Target
Visible light camera	Basler acA2500-14uc	2592×1944	30 fps	Surface defects (spatter, lack of fusion)
Infrared camera	FLIR A655sc	640×512	60 fps	Subsurface temperature anomalies (crack precursors)
Ultrasonic probe	Olympus V319-RM	5 MHz	10 fps	Internal defects (pores, interlayer cracks)

Sensor layout strategy:

Visible light and infrared cameras are mounted on the top of the SLM chamber, perpendicular to the build platform, covering a 100×100 mm² field of view;

The ultrasonic probe is embedded under the build platform and synchronized with the laser scanning path via a linear motion stage.

3.1.2 Software modules

The software is developed using C++ (Qt framework) and Python (PyTorch), with four core modules:

The data acquisition module synchronizes multi-modal data via USB3.0/Ethernet with a timestamp error <1 ms;

The preprocessing module implements denoising, illumination correction, and image registration (SIFT feature matching, registration error <1 pixel);

The fusion recognition module executes the attention-enhanced NSCT-PCNN fusion algorithm and improved YOLOv3 model;

The visualization control module displays defect location/category in real time and outputs process adjustment signals (e.g., laser power compensation) to the SLM machine.

3.2 Image preprocessing module

3.2.1 Preprocessing workflow

Denoising: For visible light images, adaptive median filtering (with a window size of 3×3–7×7) is applied to remove spatter noise; for infrared images, wavelet threshold denoising (using a soft threshold and 3 decomposition levels) is used to suppress environmental thermal noise [14];

Illumination correction: The Retinex algorithm is adopted to address the issue of "overexposed molten pool center and underexposed edges," increasing image contrast by 20%–30%;

Registration: Using visible light images as the reference, SIFT (Scale-Invariant Feature Transform) extracts 200–500 feature points, and RANSAC (Random Sample Consensus) eliminates mismatches (error threshold <2 pixels) [14].

3.2.2 Preprocessing performance validation

PSNR (Peak Signal-to-Noise Ratio) is used to evaluate image quality (higher PSNR indicates better quality). Table 4 shows the results of 500 sample images:

Table 4. Preprocessing performance (PSNR, dB)

Processing Step	Visible Light Image	Infrared Image
Raw image	28.5 ± 1.2	25.3 ± 1.5
Denoised image	32.1 ± 0.9	29.7 ± 1.1
Corrected image	34.8 ± 0.7	31.2 ± 0.8

3.3 Fusion and defect recognition module

3.3.1 Cross-Modal attention-enhanced nsct-pcnn fusion algorithm

The algorithm dynamically assigns weights to multi-modal defect features using a cross-modal attention module, with the following steps:

NSCT decomposition: Preprocessed visible light, infrared, and ultrasonic images are decomposed into 1 low-frequency subband (global information) and 6 high-frequency subbands (edge/detail information);

Attention weight calculation: First, defect response values (R_i) are computed for each high-frequency subband: $R_{visible}$ is the gradient of the visible light image ($\nabla I_{visible}$), $R_{infrared}$ is the temperature difference of the infrared image ($\Delta T_{infrared}$), and $R_{ultrasonic}$ is the echo amplitude deviation of the ultrasonic image

(|A_{ultrasonic} - \bar{A}|); then, weights are dynamically assigned via the Sigmoid function: w_i = \sigma(\alpha \cdot R_i + \beta), where \alpha = 0.8 and \beta = 0.2 (optimized via 5-fold cross-validation);

PCNN fusion: Attention weights are embedded into PCNN linking strength: \beta_{ij} = w_i \cdot \beta_0 (\beta_0 = 0.7), enhancing fusion of defect regions and suppressing background noise;

NSCT reconstruction: Fused low-frequency and high-frequency subbands are reconstructed into a single defect image.

3.3.2 Improved YOLOV3 model

To address the low detection rate of small defects in traditional YOLOv3, three optimizations are implemented:

Additional small-scale detection branch: A 52×52 detection branch (receptive field 16×16 pixels) is added to the original 13×13 (large defects) and 26×26 (medium defects) branches, adapting to <50 µm defects;

Weighted K-means anchor box clustering: Based on 28,600 defect annotations in the dataset, weighted coefficients w = \sqrt{w_{defect} \cdot h_{defect}} (square root of defect width-height product) are used to optimize 6 anchor box sizes: (12,15), (20,23), (35,38), (50,55), (70,75), (95,100);

CIoU loss optimization: IoU loss is replaced with CIoU loss, which introduces penalty terms for defect aspect ratio and center distance, improving bounding box regression accuracy by 15%–20%.

3.3.3 Offline algorithm performance comparison

Experiments are conducted on an NVIDIA RTX 3090 GPU using a test set of 2400 images (Table 5):

Table 5. Offline performance comparison

Fusion Algorithm	Recognition Model	mAP (%)	Small Defect Detection Rate (%)	Inference Speed (fps)
NSCT-PCNN	YOLOv3	89.2 ± 1.3	83.5 ± 2.1	15.3 ± 0.8
Attention-NSCT-PCNN	YOLOv3	93.5 ± 0.9	88.7 ± 1.5	14.8 ± 0.6
Attention-NSCT-PCNN	Improved YOLOv3	95.8 ± 0.7	92.3 ± 1.2	21.5 ± 0.5

4 Experiments and performance evaluation

4.1 Experimental setup and dataset construction

4.1.1 Experimental equipment and materials

SLM machine: EOS M290 (laser wavelength 1064 nm, maximum power 400 W);

Material: Ti-6Al-4V powder (chemical composition: Al 6.0%, V 4.0%, Fe 0.3%, O 0.2%, Ti balance);

Annotation tool: LabelImg, with annotations by two senior AM inspection engineers (Kappa coefficient = 0.92, indicating high consistency).

4.1.2 Dataset details

The dataset includes 12,000 multi-modal image samples (visible light, infrared, ultrasonic) with 5 defect types (Table 6):

Table 6. Dataset distribution

Dataset Split	Sample Number	Defect Distribution (%)	Process Parameter Range
Training set	8400	Pore 25, Crack 20, Lack of fusion 25, Spatter 15, Deformation 15	Laser power 180–300 W, Scanning speed 800–1600 mm/s
Validation set	1200	Same as training set	Same as training set
Test set	2400	Same as training set	Laser power 200–280 W, Scanning speed 1000–1400 mm/s

All images are resized to 640×640 pixels for model training.

4.2 Evaluation metrics and methods

4.2.1 Evaluation metrics

Precision (P) is calculated as P = \frac{TP}{TP + FP}, where TP (True Positive) is the number of correctly detected defects, and FP (False Positive) is the number of false detections;

Recall (R) is calculated as R = \frac{TP}{TP + FN}, where FN (False Negative) is the number of missed defects; mAP (Mean Average Precision) is the mean of Average Precision for all defect categories, measuring overall detection accuracy; Detection speed is represented by frames per second (fps), reflecting real-time performance; Registration error is the pixel deviation after multi-modal image alignment, evaluating data consistency.

4.2.2 Evaluation methods

Comparison experiments: The proposed system is compared with two baseline systems: (1) Single-sensor system (visible light + YOLOv3); (2) Traditional multi-sensor system (NSCT-PCNN + YOLOv3);

Stability test: The system is run continuously for 8 hours (printing 10 Ti-6Al-4V samples, 48 minutes per sample), and hourly mAP and detection speed are recorded;

Interference test: The system’s performance is tested under fan interference (wind speed 2–3 m/s) and electromagnetic interference (220 V/50 Hz).

4.3 Experimental results and analysis

4.3.1 Defect detection results

Surface defects (spatter): The fused image clearly displays spatter edges (50–100 μm), with an overlap rate >90% between the improved YOLOv3 detection box and actual defects;

Internal defects (pores): Ultrasonic images locate pores, and infrared images confirm associated temperature anomalies, increasing the pore detection rate from 83.5% (traditional method) to 92.3%;

Interlayer cracks: Combined infrared temperature gradient anomalies and ultrasonic echo mutations reduce crack length measurement error to <5% (vs. <10% for traditional methods).

4.3.2 Online Performance Comparison

Table 7 shows the online test results (average of 10 repeated experiments):

Table 7. Online performance comparison

System Type	Precision (%)	Recall (%)	mAP (%)	Detection Speed (fps)	Registration Error (pixel)
Single-sensor system	88.5 ± 1.5	82.1 ± 2.3	85.3 ± 1.8	25.7 ± 1.0	-
Traditional multi-sensor system	91.2 ± 1.2	86.8 ± 1.7	89.2 ± 1.4	15.3 ± 0.7	1.8 ± 0.3
Proposed system	94.7 ± 0.9	93.2 ± 1.1	95.8 ± 0.7	21.5 ± 0.5	0.9 ± 0.2

The proposed system outperforms baseline systems in precision, recall, and mAP, while maintaining a detection speed >20 fps for real-time SLM monitoring.

4.3.3 Stability and Anti-Interference Analysis

Stability: Over 8 hours of continuous operation, mAP decreases slightly from 95.8% to 94.2% (1.6% drop), and detection speed remains stable at 20.8–21.5 fps, indicating no significant performance degradation;

Anti-interference: Under fan interference, mAP decreases to 93.5% (2.3% drop); under electromagnetic interference, mAP decreases to 92.8% (3.0% drop), still meeting industrial detection requirements (mAP > 90%).

4.3.4 Closed-Loop Process Validation

Based on defect detection results, SLM process parameters are dynamically adjusted:

Laser power is increased from 200 W to 220 W when pore density exceeds 5 pores/mm^3;

Scanning speed is decreased from 1200 mm/s to 1000 mm/s when interlayer cracks are detected.

After adjustment, the defect rate of Ti-6Al-4V components decreases from 18.5% to 5.2%, and the tensile strength increases from 860 MPa to 966 MPa (12.3% improvement), verifying the system’s engineering value.

5 Discussion

5.1 Key findings

Multi-sensor synergy: The combination of visible light (surface), infrared (subsurface), and ultrasonic (internal) sensors achieves full-dimensional defect coverage, addressing the limitation of single-sensor systems;

Attention-enhanced fusion: The cross-modal attention module dynamically weights defect features, improving fusion accuracy by 4.3% (mAP from 89.2% to 93.5%) compared to traditional NSCT-PCNN;

Small defect detection: The improved YOLOv3 model with an additional small-scale branch and CIoU loss increases small defect detection rate by 8.8% (from 83.5% to 92.3%), which is critical for detecting <50 μm pores;

Real-time performance: The system's detection speed (21.5 fps) meets the requirements of high-speed SLM processes (scanning speed >10 mm/s), outperforming Transformer-based fusion methods (8 fps) [11].

5.2 Limitations

Ultrasonic probe frame rate: The ultrasonic probe's frame rate (10 fps) is lower than that of visible light (30 fps) and infrared (60 fps) cameras, slightly limiting internal defect detection real-time performance;

Material adaptability: The dataset only includes Ti-6Al-4V, requiring validation for other materials (e.g., aluminum alloys, superalloys);

Complex component coverage: Sensor field of view limitations cause detection blind spots in complex components (e.g., hollow structures).

5.3 Future directions

Hardware upgrade: High-frequency ultrasonic probes (>30 fps) will be adopted to synchronize multi-sensor frame rates;

Algorithm optimization: Federated learning will be integrated to train a material-adaptive model using multi-enterprise datasets, improving generalization;

3D defect localization: Structured light scanning will be combined to realize 3D defect positioning, eliminating blind spots in complex components;

Industrial integration: Collaboration with AM equipment manufacturers will be conducted to develop embedded detection modules for commercialization.

6 Conclusion

This study develops an online defect detection system for AM based on multi-sensor fusion. Key innovations include a cross-modal attention-enhanced NSCT-PCNN fusion algorithm and an improved YOLOv3 model. Experimental results show that the system achieves 95.8% mAP, 92.3% small defect detection rate, and 21.5 fps detection speed. In closed-loop control, the defect rate of Ti-6Al-4V components is significantly reduced, and mechanical properties are improved. This system provides a reliable solution for real-time, full-dimensional defect monitoring in AM, promoting the industrial application of metal AM technologies.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (Grant No. 52275346) and the Key Research and Development Program of Jiangsu Province (Grant No. BE2023006). The authors thank the Additive Manufacturing Laboratory of Southeast University for providing experimental platforms and EOS GmbH for technical support in SLM machine debugging.

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