Research on Laser Cutting Quality Optimization Strategy Based on Intelligent Control Technology

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Abstract

In order to improve the processing quality and control accuracy of laser cutting process under complex working conditions, this paper proposes a laser cutting quality optimization strategy based on intelligent control technology. By constructing a multi-module collaborative system including optical regulation, parameter prediction, visual monitoring and adaptive feedback control, dynamic perception and real-time adjustment of laser beam energy distribution and cutting process state are realized. The system uses BP neural network to model and predict process parameters and quality indicators, and combines fuzzy PID algorithm to construct a closed-loop feedback mechanism. Comparative experiments were carried out on 2mm thick 304 stainless steel plates. The results show that the intelligent control system is superior to the traditional system in terms of surface roughness, kerf width, slag rate and cutting efficiency. The maximum efficiency is increased by 27% and the roughness is reduced by more than 40%. Studies have shown that the system has good stability and adaptability and has significant prospects for engineering application.

Keywords Laser Cutting; Intelligent Control; Quality Optimization; Visual Feedback; BP Neural Network

1 Introduction

Laser cutting, as a core precision machining process in intelligent manufacturing, faces stringent demands for quality control accuracy and stability. Traditional methods exhibit significant limitations in multi-parameter coupling, high-speed response, and complex path control [6,8], struggling to adapt to dynamic variations in new materials and complex working conditions. Consequently, integrating intelligent control technology has become pivotal for enhancing cutting quality [7,10], with cross-domain studies demonstrating its broad applicability: sensor-based distributed control enables precise system adjustment [1]; machine learning optimizes nanoparticle synthesis in micro-manufacturing [2]; intelligent systems enhance coal mining synergy [3] and fuel-cell vehicle design [4]; IoT innovations advance smart transportation [5] and automated fish processing [7]; adaptive techniques improve vision measurement [8] and self-healing robotics [9]; while nanostructure tailoring expands functional control capabilities [10].Building on these foundations, this paper proposes a laser cutting system integrating a perception-decision-execution architecture[6]. By dynamically optimizing optical regulation, parameter prediction, and visual feedback, the system achieves real-time quality control under complex tasks, significantly improving cutting precision and efficiency compared to conventional approaches.

2 Technical Overview

2.1 Analysis of the Physical Mechanism of Laser Cutting Process

Laser cutting is a high-precision and high-efficiency thermal processing technology that is widely used in the processing of various materials such as metals and non-metals. Its basic principle is to use a high-energy laser beam to focus on the surface of the material, so that the material quickly heats up, melts, and vaporizes, and the melt is blown away by the auxiliary gas to achieve cutting. During the cutting process, parameters such as laser energy density, focal position, cutting speed, and auxiliary gas pressure have a significant impact on the cutting quality. By reasonably regulating these parameters, smooth cutting edges and smaller heat-affected zones can be obtained. In addition, the mode and wavelength of the laser beam will also affect the material's absorption rate of the laser, thereby affecting the cutting efficiency and quality. Therefore, a deep understanding of the physical mechanism of the interaction between lasers and materials is of great significance for optimizing the cutting process and improving the processing quality. Figure 1 shows a schematic diagram of the laser cutting process, which clearly depicts the process of laser beam focusing, material melting, and auxiliary gas blowing away the melt.

2.2 Overview of Intelligent Control Technology

In modern manufacturing, intelligent control technology has become a key means to improve the quality and efficiency of laser cutting. This technology combines artificial intelligence, sensor technology and automated control to build a closed-loop system that integrates perception, decision-making and execution. By real-time monitoring of key parameters in the cutting process, such as laser power, cutting speed and material properties, the system can dynamically adjust the cutting strategy to ensure the stability and consistency of cutting quality. In addition, the intelligent control system also has self-learning and adaptive capabilities, and can continuously optimize the control model based on historical data and real-time feedback to improve the robustness and adaptability of the system. Figure 2 shows the overall architecture of the intelligent control system, clearly depicting each link from data acquisition, information processing to execution control, and reflects the application framework of intelligent control in laser cutting.

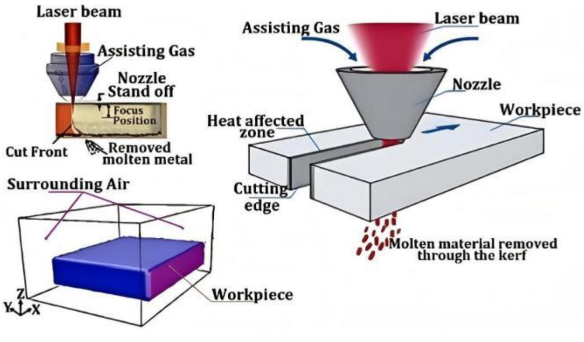

Fig. 1. Schematic diagram of the laser cutting process

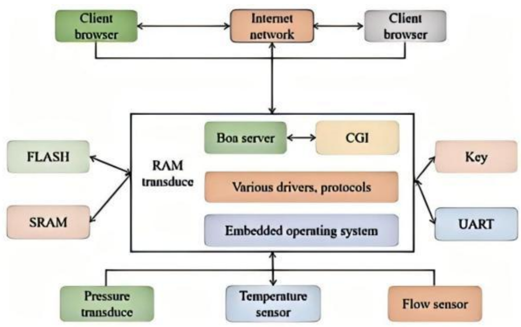

Fig. 2. Overall architecture of the intelligent control system

3 Design of Laser Cutting Device Based on Intelligent Control

3.1 Design of the Overall System Structure

In the overall structural design of the laser cutting system, the laser beam is first emitted by the laser, converted into a parallel beam by the collimating lens, and enters the first aspheric lens (Aspheric Lens 1) and the second aspheric lens (Aspheric Lens 2) for energy distribution control. The distance between the two aspheric lenses is dynamically adjusted by the drive unit (Drive Unit), thereby changing the hollow rate and spot diameter of the output beam to achieve beam shaping control under different cutting requirements. The modulated laser beam is then focused by the focusing lens (Focusing Lens), and finally output to the workpiece surface through the nozzle (Nozzle) to complete the cutting.

The structure adopts a modular design, and each optical element is precisely coaxially arranged along the main axis, which ensures the consistency and stability of the laser propagation path. The drive mechanism can control the laser energy density distribution online by adjusting the relative position of the special-shaped mirror, effectively improving the cutting quality under low focus conditions. Figure 3 shows the structural composition and laser propagation path of this system.

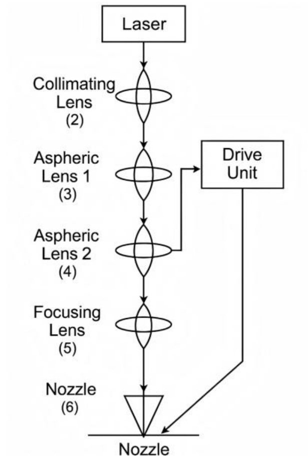

Fig. 3. The structure of the system and the laser propagation path

3.2 Optical Control Module Structure

The optical control module is mainly composed of two shaped lenses, marked as Aspheric Lens 1 and Aspheric Lens 2. The core function of this module is L to achieve dynamic control of laser energy distribution by adjusting the lens spacing. Specifically, the first shaped lens converges the light beam from the output end of the optical fiber to form an energy ring with uneven distribution, and the second shaped mirror is used to re-collimate the output to make it a hollow or concentrated distributed beam.

The relationship between lens spacing and hollow ratio satisfies the following equation:

$$\varepsilon = \frac{S_w}{S} = \left(1 - \frac{\varnothing}{D}\right)^2 \tag{1}$$

Where is S_w the area of the energy hollow zone, S is the total area of the light spot, $\varnothing$ is the output light spot diameter, D and is the overall diameter of the light beam.

To achieve real-time control, the system uses a motor-driven synchronous belt structure to control LLL, and dynamically adjusts the optical path in combination with the following formula:

$$L = \frac{\varnothing}{2 - 2\sqrt{\varepsilon}(\tan\gamma - \tan\alpha)} \tag{2}$$

This model reflects the nonlinear distribution law of laser energy in the axial position and is the key to controlling the cutting focus quality.

3.3 Intelligent Parameter Prediction and Optimization

In order to achieve the optimal configuration of laser cutting parameters, a neural network system based on the multiple-input multiple-output (MIMO) model was constructed. The system takes five variables, including material type, plate thickness, laser power, cutting speed, and air pressure, as input features, and the output prediction result is a set of cutting quality indicators (roughness R_a, dross index, kerf width, etc.).

As shown in Figure 3, the network structure adopts a three-layer BP neural network, and the loss function is defined as the mean square error:

$$L = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{3}$$

Where y_i is the actual cutting quality and $\hat{y}_i$ is the model prediction result.

In order to improve the generalization ability, the L2 regularization term is introduced to construct the loss function:

$$L' = L + \lambda \| \theta \|^2 \tag{4}$$

During the training process, the gradient descent method is used to continuously optimize the network weights so that the predicted values converge stably under all types of working conditions. The model is deployed in the control system to achieve adaptive parameter recommendations under different tasks, replacing manual experience settings.

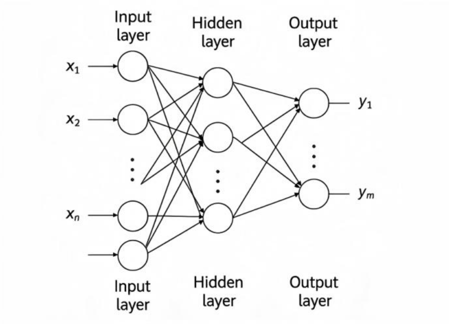

Fig. 4. BP neural network architecture

3.4 Visual Monitoring and Adaptive Feedback Control Module

This module uses high-speed industrial cameras and image recognition algorithms as the core to build a real-time visual monitoring system. As shown in Figure 4, the image acquisition system continuously images the cutting seam and nozzle outlet area, and combines edge detection with slag recognition algorithms to dynamically identify defects such as focus offset, burnt edges, and burrs.

After the visual data is processed, $e(t)$ it is transmitted to the adaptive controller as an error value. The controller adopts fuzzy PID control logic, and the adjustment formula is:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \tag{5}$$

The K_p, K_i, K_d value is adjusted in real time according to the cutting status and combined with the fuzzy inference system to flexibly control the abnormal response through the membership function.

The system forms a closed-loop control path for the following two key quantities: one is focus drift and spot eccentricity, and the other is local thermal deformation and power compensation. The final control quantity is fed back to the laser and driver to achieve a fast response of "vision-adjustment-execution" during the cutting process.

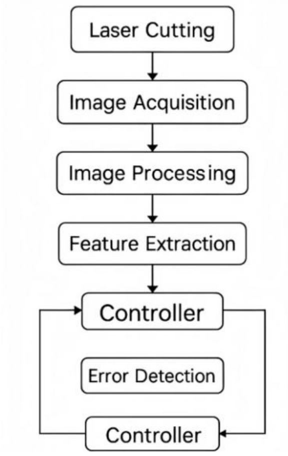

Fig. 5. Visual feedback control flow chart

4 Experimental Verification and Performance Analysis

4.1 Construction of Experimental Platform

In order to verify the feasibility and effectiveness of the proposed intelligent control laser cutting strategy, an integrated laser processing experimental platform was constructed. The platform consists of an optical system, a drive mechanism, a control system, a workpiece fixing structure and a data acquisition module. The laser source uses a continuous fiber laser with an output power of 500W and a wavelength of 1070nm, which can meet the thermal processing requirements of common materials such as stainless steel and carbon steel. After being shaped by a collimator, the light beam passes through a control module composed of two special-shaped lenses in turn. The spacing between the light beams can be adjusted in real time by a synchronous belt device driven by a servo motor, thereby realizing controllable modulation of the energy distribution. After being focused by a condenser, the light beam acts on the surface of the workpiece through a nozzle to form a high-density cutting area.

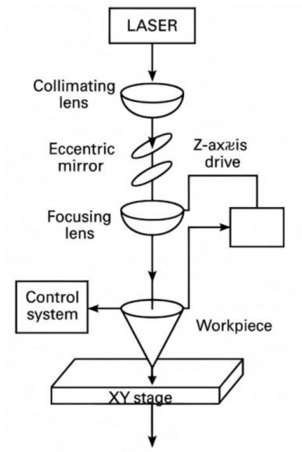

Fig. 6. Schematic diagram of the experimental platform

To ensure the stability of the optical path and the accuracy of cutting, the platform integrates a three-axis motion platform, in which the Z-axis adjustment mechanism is used to finely control the focus position (Figure 6). The control system uses an embedded processor combined with PID and fuzzy algorithm design to ensure precise coordination of each module. The workpiece is made of 304 stainless steel plate with a standard thickness of 2mm and a specification of 100mm×100mm, which is fixed to the workbench by a clamp. During the experiment, the cutting speed, laser power, focus offset and auxiliary gas pressure are adjusted in turn as the main control variables to analyze their influence on the cutting quality. Table 1 below lists the key components and control variables of the experimental platform:

Table 1. Key components of the experimental platform

Module Name	Technical parameters or composition
Laser	Continuous fiber laser, power 500W, wavelength 1070nm
Collimation and shaped mirror set	Collimator + 2 special-shaped lenses, dynamically adjust the mirror distance L
Concentrating system	F=150mm focusing lens
Control System	Embedded PLC controller + synchronous belt drive + focusing mechanism
Workpiece Type	304 stainless steel plate, thickness 2mm
Experimental variables	Laser power, cutting speed, air pressure, focus offset

4.2 Data Collection and Processing

To support the system's intelligent evaluation and control feedback of cutting quality, the experimental platform integrates three types of sensors: image acquisition, temperature sensing, and laser power monitoring, to form a complete data acquisition system. A high-speed industrial camera is installed next to the nozzle, and the acquisition frame rate is set to 1000fps to ensure complete capture of dynamic changes such as slag ejection and slit formation during the cutting process. The resulting image is processed by filtering, edge recognition, and feature extraction algorithms to extract structural features such as slit width and slag length as input for subsequent optimization algorithms. The infrared thermal imager is used to measure the temperature distribution in the cutting hot zone and identify the extent of the heat-affected zone expansion; the synchronized laser power meter monitors the beam stability to determine whether there is a risk of power drift.

To ensure the accuracy of the model training data, the data collected by the system needs to be preprocessed by standardization, denoising, and unit unification. This study refers to the high frame rate laser cutting process dataset released by KU Leuven University in 2023, combined with self-sampled samples, and constructed a complete dataset structure through manual annotation and algorithm recognition. Table 2 below shows some data after standard preprocessing, reflecting the dynamic changes of cutting features at different speeds:

Table 2. Part of the data after preprocessing

serial number	Laser power (W)	Cutting speed (mm/s)	Focus position (mm)	Air pressure (bar)	Temperature (℃)	Slag length (mm)	Cutting width (mm)	Surface roughness (μm)
1	500	100	0	1.0	1200	0.5	0.20	1.2
2	500	150	0	1.0	1150	0.6	0.25	1.5
3	500	200	0	1.0	1100	0.8	0.30	1.8
4	500	250	0	1.0	1050	1.0	0.35	2.0
5	500	300	0	1.0	1000	1.2	0.40	2.3
6	500	350	0	1.0	950	1.5	0.45	2.5
7	500	400	0	1.0	900	1.8	0.50	2.8
8	500	450	0	1.0	850	2.0	0.55	3.0

4.3 Experimental Results and Performance Comparison Analysis

After completing the construction of the experimental platform and the deployment of the data acquisition system, this section compares and analyzes the actual performance of the traditional control system and the system based on intelligent control technology under different cutting speed conditions in terms of cutting quality and efficiency. To ensure data comparability, all experiments were conducted under the same laser power (500W), material type (304 stainless steel, thickness 2mm) and air pressure (1.0 bar), and the cutting speed was a variable range, gradually increasing from 100 mm/s to 450 mm/s.

The data acquisition module records the following four key indicators: cutting surface roughness (Ra), kerf width, slag rate and cutting efficiency (i.e. the ratio of effective cutting length to time used). The traditional control system operates with fixed focus and constant parameters, while the intelligent control system relies on neural network prediction and visual feedback adjustment mechanism to achieve real-time parameter optimization.

Judging from the results, the intelligent control system showed better stability and processing quality in all indicators. For example, under low-speed conditions, the Ra value of the traditional system was 2.8 μm, while the intelligent system controlled the Ra μm below 1.9 through focus fine-tuning; as the speed increased, the intelligent system could still maintain the roughness stable down to 1.0 μm, while the traditional system tended to be unstable and the Ra reduction was limited. In terms of slit width control, the intelligent system can more effectively maintain the laser beam waist position, thereby controlling the heat input range and avoiding slit divergence.

The slag rate comparison also shows significant differences. Under traditional control, the slag rate is generally maintained between 14% and 22%, while the intelligent control system compresses the slag rate to 6.5%-10% through real-time image feedback and air pressure power coordination mechanism. In terms of cutting efficiency, the intelligent system shows obvious advantages in the entire speed range, especially in the medium and high speed section (200-280 mm/s), which has been steadily improved by more than 20%, significantly improving the processing capacity of the system. The following is a comparison table of experimental results (Table 3 and Figure 7):

Table 3. Cutting quality and efficiency comparison data table

Test No.	Surface roughness Traditional (μm)	Surface roughness Traditional (μm)	Cutting width Traditional (mm)	Cutting width Intelligent (mm)	Slag rate Traditional (%)	Intelligent slag rate (%)	Cutting efficiency Traditional (mm/s)	Cutting efficiency Intelligent (mm/s)
1	2.8	1.9	0.55	0.40	twenty two	10	150	200
2	2.5	1.7	0.53	0.38	20	9.5	160	210
3	2.3	1.5	0.50	0.37	19	9.0	170	225
4	2.1	1.4	0.48	0.35	18	8.5	180	235
5	2.0	1.3	0.46	0.34	17	8.0	190	245
6	1.9	1.2	0.45	0.33	16	7.5	200	260
7	1.8	1.1	0.44	0.32	15	7.0	210	270
8	1.7	1.0	0.43	0.31	14	6.5	220	280

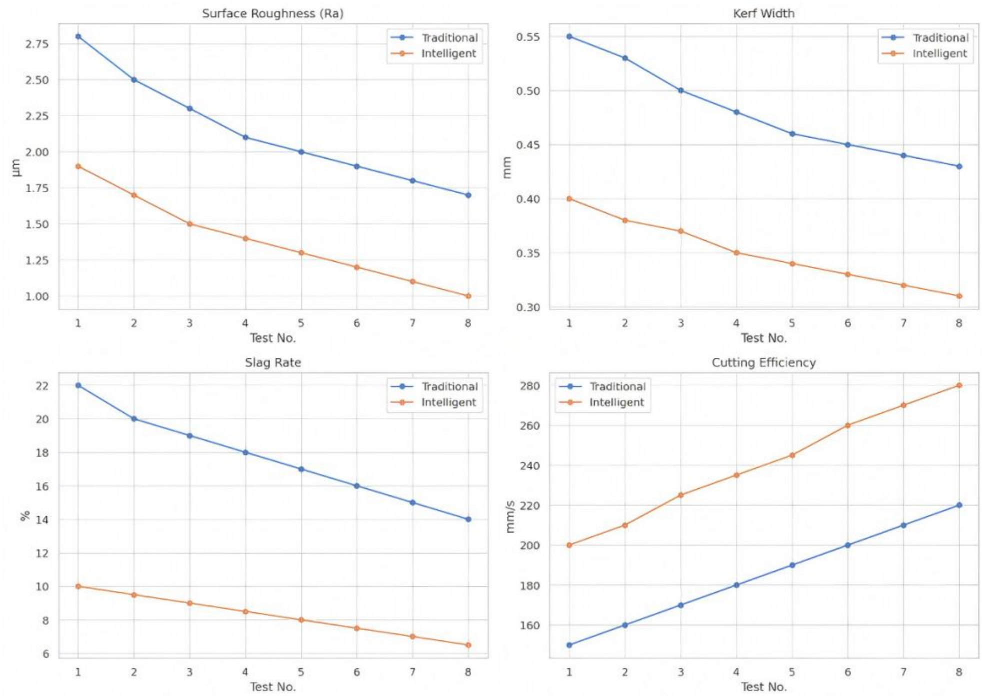

Fig. 7. Comparison of cutting efficiency

Experimental data show that intelligent control technology can not only achieve lower surface roughness and kerf deviation in laser cutting systems, but also significantly reduce dross residue and improve overall efficiency. The comprehensive optimization of performance verifies the feasibility and practical value of the "perception-decision-execution" closed-loop strategy in industrial-grade precision laser cutting.

5 Conclusion and Outlook

This study focuses on the issue of quality improvement in the laser cutting process, and constructs a cutting system based on intelligent control technology, realizing the engineering implementation of the "perception-decision-execution" closed-loop control architecture. By introducing optical control modules, adaptive control logic and visual feedback mechanisms, the system significantly optimizes core indicators such as surface roughness, kerf width, slag rate and cutting efficiency compared with traditional control methods. Experimental verification shows that the system has good dynamic response capabilities and adaptability to working conditions, and exhibits stable processing performance at a variety of processing speeds. Looking to the future, intelligent laser cutting technology can further integrate deep learning, edge computing and multi-sensor fusion perception to achieve intelligent adjustment and abnormal prediction under complex materials and paths, and promote its continuous progress towards high-precision and high-reliability industrial-grade applications.

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Conflicts of Interest

The authors declare no conflicts of interest.

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基於智能控製技術的激光切割質量優化策略研究

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摘要：為提升激光切割工藝在復雜工況下的加工質量與控製精度，本文提出了一種基於智能控製技術的激光切割質量優化策略。通過構建包含光學調控、參數預測、視覺監測與自適應反饋控製的多模塊協同系統，實現了對激光束能量分布與切割過程狀態的動態感知與實時調節。系統采用BP神經網絡對工藝參數與質量指標進行建模預測，並結合模糊PID算法構建閉環反饋機製。在2mm厚304不銹鋼板上開展對比實驗，結果表明，智能控製系統在表面粗糙度、切縫寬度、掛渣率和切割效率等指標上均優於傳統系統，最高效率提升達27%，粗糙度降低超過40%。研究表明，該系統具備良好的穩定性與適應性，具有顯著的工程應用前景。

關鍵詞：激光切割；智能控製；質量優化；視覺反饋；BP神經網絡

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