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Research Progress of Weld Seam Tracking Technology Based on Visual Sensing

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Abstract. Welding serves as a core joining process in high-end manufacturing. The teach-and-reproduce mode adopted by traditional automated welding can hardly adapt to workpiece assembly errors, welding thermal deformation and complex on-site disturbances, thus failing to meet the demands of high-precision and intelligent welding. Visual sensing technology features non-contact measurement and high detection accuracy, acting as the core support for visual weld seam tracking and a research hotspot in intelligent welding. This paper systematically elaborates the principle and system composition of visual weld seam tracking, and summarizes mainstream sensing schemes including passive vision, active vision and active-passive combined vision. It also analyzes the research progress of three key technologies: weld image processing, recognition and positioning algorithms, and tracking control strategies. Two core dilemmas of current technologies are pointed out: insufficient anti-interference performance in complex environments and poor adaptability to complex welds. Combined with the development trends of deep learning and multi-sensor fusion, this paper forecasts the development directions of visual weld seam tracking towards intelligence, multi-dimensional perception and end-to-end intelligent decision-making, providing a reference for the engineering application of this technology in high-end manufacturing.

Keywords: visual sensing, weld seam tracking, intelligent welding, image processing, welding

1. Introduction

Welding is a core joining process in modern manufacturing. It is widely used in high-end fields including aerospace, rail transit, ship engineering and new energy equipment. Welding quality and efficiency directly determine the structural performance and service life of key products. Traditional automated welding adopts the teach-and-reproduce mode. It cannot adapt to workpiece assembly errors, welding thermal deformation and strong on-site interference such as arc light, smoke, dust and spatter. These problems easily cause weld deviation and poor formation. They can no longer meet the high-precision and intelligent requirements of modern high-end manufacturing.

Visual sensing technology has become the core solution to the above dilemmas. It has obvious advantages of non-contact measurement, rich information and high detection accuracy. In recent years, this technology has developed rapidly with the integration of image processing, artificial

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intelligence and robot control. It has become a key research field to promote the intelligent upgrading of welding. Therefore, it is of great theoretical value and engineering significance to systematically sort out its research progress. However, existing reviews have obvious limitations. Most of them only focus on a single technical link. Few reviews comprehensively sort out the whole technical chain from sensing to control. The summary of bottlenecks such as poor anti-interference and complex weld adaptation is not in-depth enough. This paper systematically reviews the research status of visual weld seam tracking. It sorts out the core technical routes of sensing, image processing, recognition and tracking control. It summarizes the existing technical difficulties. Finally, it forecasts the future development trends of the technology, so as to provide a reference for its engineering application in high-end manufacturing.

2. Principle and system composition of visual weld seam tracking technology

2.1. Basic principle of visual sensing

Visual sensing is the core perceptual foundation of visual weld seam tracking, which is based on optical imaging, machine vision and spatial coordinate mapping. It acquires, analyzes, and quantifies visual information from the welding zone in a non-contact fashion, supplying precise spatial data for weld localization and trajectory tracking. Optical images of the welding region are captured by industrial cameras, where continuous optical signals are converted into discrete digital images through photoelectric conversion and analog-to-digital (A/D) sampling. By means of camera calibration and perspective projection transformation, a precise correspondence between image pixel coordinates and the physical coordinates of the welding workspace is established, allowing dedicated algorithms to extract weld geometric features from the processed images. The core technical objective is to suppress imaging disturbances induced by arc glare, fume, molten droplet spatter, and other welding-related interferences. This is implemented by optimizing the optical system architecture and tuning imaging parameters, so as to ensure real-time and accurate acquisition of weld position data. Visual sensing acts as a vital bridge between physical welding scenarios and digital information processing. It provides the essential positional perception for weld tracking and lays a solid data foundation for subsequent deviation calculation and trajectory correction, which serves as a fundamental prerequisite for the intelligent and automated operation of the visual weld seam tracking system.

2.2. Overall system composition

The visual weld seam tracking system is a core closed-loop control system for intelligent welding. With visual sensing as the core perception method, it enables the welding torch to track weld trajectories accurately in real time through image acquisition, processing, deviation calculation and motion regulation. It effectively solves weld deviation and poor formation in traditional welding, and meets the high-precision welding requirements of aerospace, rail transit and other high-end manufacturing fields.

The system consists of four core components: visual sensing unit, image processing unit, motion control unit and actuator. The independent operation and collaborative cooperation of these units determine the overall accuracy and real-time performance of the tracking system. Wang et al. constructed an integrated test platform combining robotic welding and laser vision sensing, as illustrated in Figure 1 [1]. This platform consists primarily of Fronius TPS 4000 Cold Metal Transfer (CMT) advanced welding equipment, ABB IRB 1410 industrial robot and a special control cabinet.

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The Fronius TPS 4000 welding machine features centralized parameter adjustment; only the wire feeding speed requires manual configuration, and the system will automatically optimize and match the welding current and voltage to guarantee the coordinated matching of welding parameters. The laser vision sensor is fixed on the robot's end execution mechanism, constituting an Eye-in-Hand structure, which mainly comprises an AVT Manta G-283C POE industrial industrial charge-coupled device (CCD) camera, a laser generator and an optical filter.

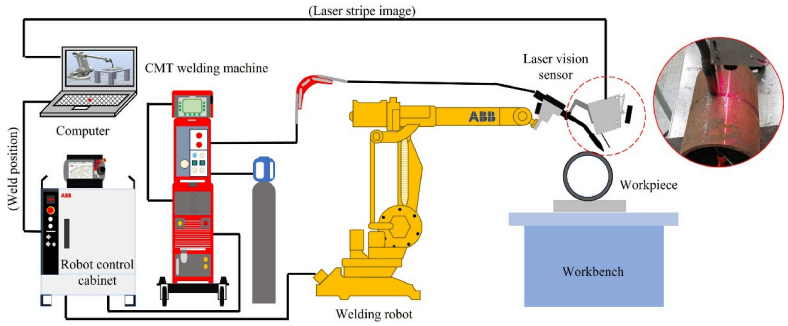

Figure 1. Integrated test platform combining robotic welding and laser vision sensing system [1]

Visual weld seam tracking has become a core technology for welding automation and intelligence. Laser structured light is the mainstream approach, while passive vision and AI-based vision are developing in parallel. The tracking accuracy, real-time performance and anti-interference performance of the technology have been significantly improved, and it has been widely used in new energy, engineering machinery, rail transit, shipbuilding and other fields. Domestic solutions have matured rapidly and realized large-scale domestic substitution of imported technologies, effectively improving the consistency of welding quality and production efficiency. In the future, the technology will evolve towards multi-modal sensor fusion, teaching-free autonomous perception, high-speed and high-precision dynamic tracking, full closed-loop quality control, lightweight design, low cost and high integration.

2.3. Main visual sensing methods

Visual sensing approaches applied to weld seam tracking can be generally classified into passive and active types. Passive visual sensing directly collects images of the welding region under natural light or arc illumination, featuring a simple structure and low cost. Active visual sensing irradiates the weld area with active light sources such as lasers and stripe lights, obtaining clearer imaging features and higher measurement accuracy. The two methods have their own advantages and limitations, and are suitable for different welding scenarios. Two intelligent systems for real-time control of weld bead geometry for GMAW were developed by Girón-Cruz et al. where a passive vision system with sensor fusion was used to control bead width and height, and an active vision system was used to control penetration [2]. The deposition pool and structured light stripes can be captured in a single image using a single CCD camera. A series of image processing algorithms were developed to detect the deposition size in real time. The experimental results show that the measurement error of the pool height is within ±0.1 mm and the measurement error of the pool width is within ±0.2 mm. A Wide Dynamic Range (WDR) vision sensor was used to obtain real-time images of the welding process. A weld seam tracking algorithm using Window Information Fusion (WIF) was proposed to detect the deviation of the welding torch position in real time during the arc welding weaving process. Local Feature Moving Window Recognition (LMWR) algorithm was used to identify the groove center and Kalman filter to estimate the deviation. The algorithm was tested on the

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horizontal weld seam, and the accuracy of the tracking was ±0.47 mm [3]. Overall, active visual sensing has become the mainstream because of its high precision, while passive visual sensing has the advantages of low cost and simple operation in welding. The focus of research is to improve the robustness of the measurement method to different welding materials and welding conditions, and the system's resistance to interference.

3. Research status of key technologies of visual weld seam tracking

3.1. Weld image processing

Weld image processing is based on digital image processing and machine vision. Its core is to process original images disturbed by arc light, smoke and dust with a series of algorithms, so as to suppress noise, enhance features and extract key weld geometric information, providing effective data for weld recognition and positioning. Technical means of weld image processing mainly include image preprocessing (filtering, threshold segmentation, image enhancement, etc.) and feature extraction (edge detection, contour fitting, geometric operation, etc.). To satisfy the image processing demands under complex welding scenarios, intelligent approaches including deep learning semantic segmentation and feature detection are introduced. Jiao et al. explored the energy distribution characteristics of arc light, and defined the optical parameters of composite dimming processing and near-infrared narrowband filtering. They built an arc radiation model and chose a suitable high-speed CCD camera to develop a visual capture system, which notably weakened the interference of arc radiation on the imaging of the molten pool. By integrating Hough transform, corner detection, coordinate transformation and camera calibration, the researchers finished binocular image calibration and lossless transformation between pixel coordinates and physical coordinates. The developed visual sensing system can markedly restrain the interference caused by arc light and welding fumes. Meanwhile, the FCM-Sobel fusion algorithm can extract complete, continuous and low-noise edges of the molten pool with high precision in geometric feature acquisition [4]. The composite filtering and visual sensing framework is shown in Figure 2.

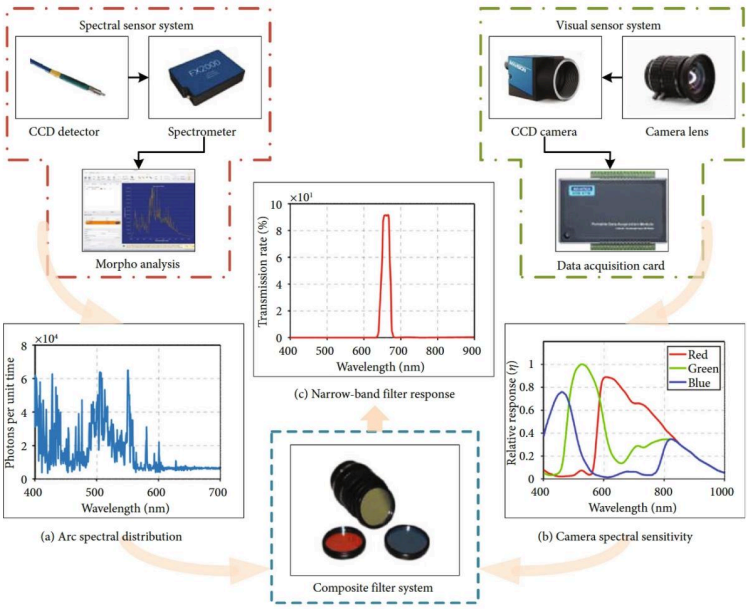

Figure 2. Analysis of optimal waveband for composite filtering system based on spectral and visual sensing systems [4]

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Lu et al. employed a refined bilateral filtering method to reduce noise in images while preserving edge details [5]. For noise reduction and contrast improvement, the researchers integrated the contrast-limited adaptive histogram equalization (CLAHE) algorithm, Gaussian mask, and layered noise reduction. Their method was validated, and performance improvements were substantiated in terms of both peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM).

Currently, the processing of weld images shows an advanced form of research characterized by the integration of traditional and intelligent algorithms. Optimized classic filtering and edge detection algorithms continue to dominate the processing of generalized weld conditions, while real-time implementation and practicality are maintained. The use of lightweight deep learning models has advanced research in the processing of images of complex and highly interfered welding scenarios, and has enhanced the accuracy and robustness. The current focus of research is the trade-off between accuracy and real-time performance in engineering applications of algorithms and their integration. The main focuses of the field are the use of anti-jamming techniques in extreme working conditions, general algorithms for different welding types, and real-time integration with tracking control.

3.2. Weld recognition and positioning algorithm

The weld recognition and positioning algorithm is a core module of visual weld seam tracking. It analyzes and calculates the extracted weld feature information to accurately identify and solve weld position, groove shape and deviation. The operational efficiency and positioning accuracy of the algorithm directly determine the real-time performance and precision of the tracking system. Li et al. proposed a deep learning-based intelligent detection robot system for weld recognition and tracking [6]. The robot is equipped with Mecanum wheels and permanent magnets to achieve stable adsorption on metal wall surfaces. Mask R-CNN is employed to implement weld instance segmentation, and high-precision extraction of the weld path is realized by integrating image processing methods with the Hough transform technique. The complete procedure for weld gap identification and tracking consists of four key stages: capturing welding images with a camera, identifying welds through a deep learning network, extracting and fitting weld paths, and controlling the robot to track the weld path according to the path information. The workflow of weld seam recognition and tracking is shown in Figure 3.

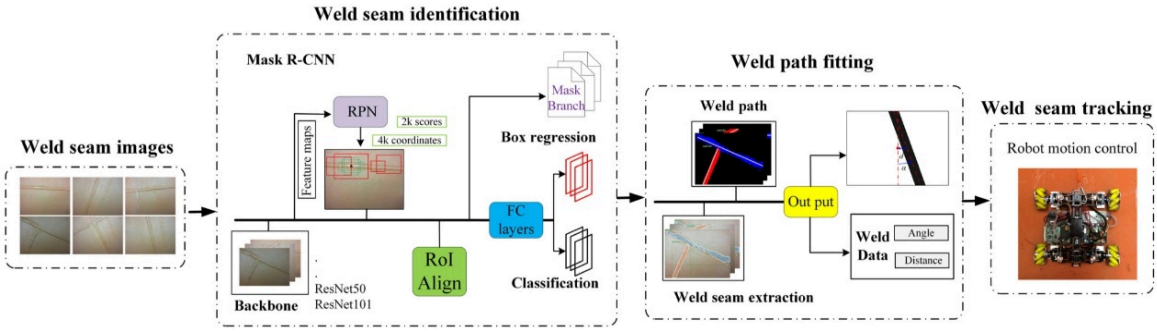

Figure 3. Workflow of weld seam recognition and tracking [6]

Jing et al. put forward a measurement scheme for weld identification and model reconstruction aimed at remanufactured blades, which relies on a self-developed binocular vision platform [7]. Preliminary coarse positioning was adopted to cut down the computing load of 3D reconstruction and simplify the follow-up point cloud processing procedure. By virtue of point cloud segmentation

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with region growing algorithm and point cloud normal vector filtering, accurate weld localization was achieved, and a genuine weld model with precise boundaries was acquired. The average boundary error derived from this method is lowered by roughly 0.263 mm relative to conventional approaches.

Wang et al. developed a high-efficiency computation approach for the curvature of curve trajectories [8]. Test outcomes demonstrate that the presented image algorithm model combined with minimum enclosing rectangle fitting can effectively recognize the weld characteristics of tank walls and realize high-precision feature localization. The position error is limited to less than 3 mm, and the azimuth error is kept below 3°, which reflects excellent precision and stability.

At present, weld recognition and positioning algorithms have evolved from manual feature extraction methods (traditional threshold segmentation, edge detection, Hough transform) to intelligent detection systems. These systems combine active visual sensing (laser structured light, binocular vision) with deep learning models such as Mask R-CNN and You Only Look Once (YOLO) series, and their accuracy, real-time performance and robustness have been greatly improved. They can efficiently complete the accurate recognition and 3D positioning of regular welds and complex curved welds, and have been applied in large storage tank detection, aero-engine blade remanufacturing, automatic welding and other engineering scenarios. Indicators such as positioning error and processing efficiency can meet industrial application requirements.

3.3. Tracking control strategy

The control strategy of tracking is the cornerstone of real-time weld tracking. Based on the error information of the position deviation of the weld, the control strategy adjusts the position of the welding robot (or welding torch) by calculating the adjustment amount of the actuator through a control algorithm. The control strategy's speed and robustness determines the stability of tracking.

During welding, oscillations are transferred to each joint of the manipulator and generate load torque disturbances, which will cause the changing of damping ratio and natural frequency of the control system, resulting in difficulty of tracking control. In order to address this issue, Zou et al. proposed a real-time seam tracking control system of line laser visions and an adaptive fuzzy controller for robotic welding [9]. The system acquires weld geometric features by adaptively adjusting the region of interest, establishes the kinematics model of the welding robot, and determines the speed adjustment of the motor drive. The coordinate transformation theory is used to dynamically adjust the position and posture of the welding torch. Lyapunov stability criteria are applied, and the fuzzy Proportional-Integral-Derivative (PID) parameters are modified based on torch position to accommodate the weld errors, keep the damping ratio and natural frequency stable, and achieve stable weld tracking control. Nam et al. proposed a new vision-to-code model that can directly generate control codes from a single weld image and achieve fully automatic weld tracking control, without additional image processing or alignment rules [10]. A field-specific dataset was built containing executable C# codes for the grayscale weld images, enabling the model to learn the mapping between visual features and device-level commands. The deep learning model comprises a CNN-based visual feature encoder, a non-autoregressive Transformer-based decoder and a self-designed code-generation tokenizer. The proposed system was successfully implemented in butt welding tests: multiple-mode fiber lasers were used to weld aluminum alloys with various weld shapes and surface textures. This end-to-end system bridges the gap between visual feature recognition and welding control instruction generation, providing a new way for vision-based intelligent welding automation.

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Currently, the weld tracking control is fast evolving towards adaptive, data-driven and end-to-end autonomous decision-making. It will further develop into multi-sensor integration, edge computing-based real-time control and complete closed-loop autonomy, thus achieving higher adaptability to complex working environments and unmanned welding ability.

4. Technical difficulties and existing problems

Visual weld seam tracking technology has achieved remarkable development, but it still faces many technical difficulties in practical industrial application. The core problems are insufficient anti-interference performance in complex environments and poor adaptability to complex welds, which directly restrict the engineering implementation and large-scale promotion of the technology.

Many researchers have pointed out the severity of these problems. Although some optimization schemes have been proposed, a universal solution has not yet been formed. Solving the technical challenges caused by complex working conditions and complex welds is the core task for the subsequent development of visual weld seam tracking. Strong arc light, high-temperature smoke, metal spatter and thermal deformation are the main environmental interferences for visual weld seam tracking. These factors blur weld images and cause feature loss, reducing the accuracy of feature extraction, recognition and positioning, and even leading to the failure of the tracking system. Insufficient anti-interference performance has become a major obstacle to the engineering application of the technology. Strong arc light and spatter are generated during welding, showing uneven distribution and irregular bright spots or blocks in images. Their random positions and shapes seriously affect the accuracy of weld corner recognition algorithms. Examples of high-noise laser welding images are shown in Figure 4 [11].

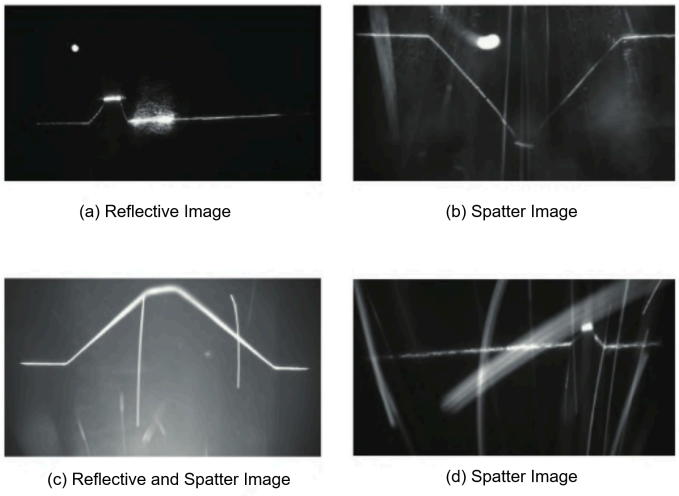

Figure 4. Examples of weld seam and high-noise laser images [11]

In high-end manufacturing, complex welds such as curved welds, variable groove welds and lap welds are increasingly used. Existing visual weld seam tracking technology performs well in tracking conventional straight welds, but has poor adaptability to complex welds. It is mainly characterized by difficult feature extraction, low positioning accuracy and poor tracking stability, which cannot meet the welding requirements of complex welds.

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5. Development trend and prospect

The future development of visual weld seam tracking will move towards intelligence and multi-dimensional perception. The in-depth application of deep learning and intelligent recognition, as well as the technological breakthrough of multi-sensor information fusion, have become two core trends. Their combination will greatly improve the robustness, real-time performance and engineering adaptability of the technology under complex working conditions. In terms of deep learning and intelligent recognition, lightweight models such as Mask R-CNN and YOLO will be continuously optimized and deployed in edge computing to solve the problem of complex weld feature extraction. The technology will develop towards end-to-end intelligence, realizing direct mapping from visual input to control instructions. Anti-interference models will be trained with massive industrial welding datasets to realize full automation and generalization from weld recognition to motion control. In terms of multi-sensor information fusion, visual sensing will be integrated with spectral, force, temperature and other sensing technologies. Multi-dimensional data such as weld position, welding temperature field and torch stress will be fused to realize full closed-loop control of tracking and quality. The complementary fusion of active vision and passive vision will be promoted, and professional data fusion algorithms will be adopted to reduce measurement errors and give full play to the advantages of different sensing methods.

Overall, deep learning and intelligent recognition provide more accurate and intelligent perception and decision-making capabilities for visual weld seam tracking, while multi-sensor information fusion breaks through the limitations of single sensing. Their deep integration will promote the development of visual weld seam tracking towards unmanned, high-precision and full closed-loop intelligent welding, better meeting the welding demands of aerospace, rail transit and other high-end manufacturing fields.

6. Conclusion

This paper comprehensively reviews visual weld seam tracking technology. The technology is based on optical imaging and machine vision, forming a closed-loop system composed of visual sensing, image processing, motion control and actuator units. A sensing system has been formed with active vision as the mainstream, passive vision as the supplement and active-passive combined vision as the innovation direction. In terms of key technologies, weld image processing has realized the integration of traditional algorithms and lightweight deep learning models; weld recognition and positioning have been upgraded from manual feature extraction to intelligent detection systems; tracking control strategies have evolved towards adaptive, data-driven and end-to-end intelligent decision-making. The accuracy, real-time performance and robustness of various technologies have been significantly improved. Meanwhile, the technology still faces prominent problems in industrial application. The degradation of image quality caused by strong arc light, smoke, spatter and other interferences, as well as the difficulty in feature extraction and tracking of complex welds such as curved welds and variable groove welds, are still the core factors restricting the engineering promotion of the technology. Existing optimization schemes have not yet formed a universal solution.

In the future, the development of visual weld seam tracking will take the in-depth application of deep learning and multi-sensor information fusion as two core directions. The deployment of lightweight intelligent models in edge computing and end-to-end vision-to-control instruction mapping will address the challenges of complex weld perception and decision-making. By relying on the integration of vision with spectral, force, temperature, and other sensing technologies, along

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with the synergistic integration of active and passive vision, the system can facilitate complete closed-loop management of weld seam tracking and welding quality, thus addressing the inherent drawbacks of single-sensor schemes. The deep integration of the two core technologies will promote visual weld seam tracking towards unmanned operation, high speed, high precision, lightweight design, and integrated development, further improving its adaptability to complex working conditions and large-scale engineering applications. It will provide core technical support for the intelligent upgrading of welding technology in high-end manufacturing and boost the automation and intelligent development of the manufacturing industry.

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