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OPTIMISATION AND ADAPTIVE CONTROL STRATEGIES FOR WELDING ROBOT SYSTEMS

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Abstract

This paper delves into the evolving landscape of welding robotics, particularly the integration of adaptive control strategies for optimising human-robot interaction. Collaborative robotics (cobotics) underscores the significance of adaptive control for secure effective and safe cooperation between humans and robots in welding tasks. Past research highlights optimisation techniques such as model-based optimization and genetic algorithms, alongside adaptive control strategies that dynamically adjust parameters based on real-time feedback. These advancements promise enhanced safety, efficiency, and competitiveness in industrial welding automation.

Keywords*: welding robotics, adaptive control, human-robot interaction, optimization techniques.*

1. Introduction

Robotics is a relatively nascent discipline compared to its counterparts in the scientific realm. At its core, a robot encompasses an amalgamation of technologies such as motors, sensors, and computing systems. The inception of robotics occurred when these individual technologies reached a level of maturity that could be integrated harmoniously. A distinguishing aspect of robotics lies in its dependence on technological advancements to conceive and explore novel applications. This inherent reliance injects an element of excitement into the field, as it continually evolves in tandem with technological progress **[1]**.]. Undoubtedly, robotics has achieved a level of maturity for specific tasks within various environments, a facet that the industry extensively leverages to bolster productivity.

One of the foremost challenges confronting robotics lies in scenarios where robots interact physically with humans, a realm ripe with promise. While robots are commonly employed in industrial settings, their utilization often involves isolating them within cells to ensure the safety of human workers. Nonetheless, numerous tasks remain ripe for automation, necessitating human operators who possess the adaptability to navigate complex situations that robots may not fully address **[1]**. As a response to this, cobotics, which facilitates collaboration between humans and robotic counterparts, has emerged. Despite its considerable potential, cobotics is still in its infancy, with safety concerns surrounding human-robot interactions at the forefront **[2]**.

Interestingly, the foundational issue inherent in such human-robot interaction predates the inception of robotics itself and stems from the realm of cybernetics. Originating during World War II, cybernetics sought to devise systems capable of predicting and accommodating human responses to robotic actions. Notably, Norbert Wiener pioneered this field with the creation of an automatic pilot system named the "predictor," designed to anticipate a pilot's evasion trajectory against anti-aircraft projectiles. Wiener's seminal work, "Cybernetics or Control and Communication in Animals and the Machine," laid the groundwork for this research domain by presenting a theory of control and communication applicable to both biological organisms and machines **[3].** It is within this framework that research on robotics in interaction with humans finds its roots.

Overall, Industrial robots are distinguished from more traditional production and assembly equipment in particular by their ability to carry out many different tasks. To carry out these various tasks, the industrial robot must often make configuration or tool changes or even make movements while taking into account its current state and the history of the production parts. This is all the more true in a dynamic scheduling environment with the possible need to change a decision or interrupt current tasks. A realistic and precise scheduling model should take into account these state change operations and the specificities of the different tasks carried out (duration, occupied capacity, etc.) [4].

Moving to one of the ultimate cobotics fields, the welding robot has control systems that reflect a significant evolution toward advanced automation and precision. Traditional control systems relied heavily on predefined trajectories and fixed parameters, limiting their adaptability to variations in welding conditions and workpiece geometries. However, recent advancements have revolutionized this landscape. Modern welding robot control systems incorporate sophisticated sensor technologies such as vision systems, laser scanners, and force/torque sensors, enabling real-time feedback and adaptive control. These systems utilize advanced algorithms, including machine learning and artificial intelligence, to optimize welding parameters and trajectories dynamically. Furthermore, collaborative robots (cobots) with advanced safety features have emerged as a prominent trend, allowing for human-robot collaboration in welding tasks [5]. Integration with cloud computing and data analytics facilitates remote monitoring, predictive maintenance, and continuous improvement of welding processes. Overall, the current state-of-the-art of welding robot control systems emphasizes flexibility, efficiency, and quality, paving the way for increased productivity and competitiveness in industries reliant on welding technology [6].

Traditional control methods in welding robot systems face several challenges that hinder their effectiveness in meeting the demands of modern manufacturing environments [5]. One significant challenge is their limited adaptability to variations in welding conditions, such as changes in material properties, joint geometries, or environmental factors like temperature and humidity. Traditional controllers often rely on predefined trajectories and fixed parameters, making them ill-equipped to handle dynamic situations encountered in real-world welding applications. This rigidity can lead to issues such as poor weld quality, inconsistent bead profiles, and increased rework or scrap rates. Moreover, traditional controllers cannot respond in real time to disturbances or anomalies during the welding process, resulting in reduced productivity and efficiency. Additionally, these control methods may struggle to optimize welding parameters for different materials or welding techniques, leading to suboptimal performance and increased operational costs. In summary, the challenges faced by traditional control methods highlight the need for more adaptive, intelligent, and flexible approaches to welding robot control to address the complexities of modern manufacturing requirements effectively [7].

1.1. State of the art

Past studies and research that focus on optimization and adaptive control within the welding domain have achieved notable progress in enhancing the performance, efficiency, and overall quality of welding operations. Extensive investigations have been conducted into optimization methodologies, targeting diverse facets of welding processes ranging from trajectory planning and parameter adjustment to resource distribution. Utilizing mathematical optimization frameworks such as genetic algorithms, particle swarm optimization, and simulated annealing, researchers have endeavoured to fine-tune welding parameters such as voltage, current, travel speed, and wire feed rate [8]. The primary objective of these optimization endeavours is to mitigate common welding defects including porosity, undercutting, and spatter, while simultaneously maximizing productivity and weld integrity [9].

Adaptive control strategies have also been a focus of research, aiming to dynamically adjust control parameters based on real-time feedback from sensors and environmental conditions [8]. Adaptive control techniques, such as model predictive control, fuzzy logic control, and neural networks, enable welding robots to adapt to changes in workpiece geometry, material properties, and welding conditions. By continuously monitoring key process variables, such as arc voltage, welding current, and torch orientation, adaptive control systems can compensate for disturbances, optimize weld bead geometry, and improve overall process stability and robustness [9].

Furthermore, research efforts have explored the integration of advanced sensing technologies, such as vision systems, laser scanners, and thermal imaging cameras, to provide comprehensive feedback for adaptive control algorithms. These sensing technologies enable welding robots to accurately detect joint misalignments, seam tracking errors, and surface irregularities, facilitating precise control and correction during the welding process [5]. Overall, previous research on optimization and adaptive control in welding has demonstrated the potential to significantly enhance the performance and efficiency of welding processes, paving the way for the development of more advanced and intelligent welding robot systems capable of meeting the demands of modern manufacturing industries [8].

The focus of this research is on the development of intelligent control techniques for welding automation. The research scope encompasses the investigation of how to control the welding path and the weld pool geometry in real time. The objectives of the research are classified into three categories: problem formulation, optimization, and adaptive control. First, a physical process and mathematical model will be investigated and developed to describe the dynamic behavior of the welding process. Then a series of optimization and adaptive control techniques will be studied and developed to effectively and efficiently control the welding process. Once the intelligent control strategies are developed, an experimental validation will be conducted to verify the correctness and effectiveness of the proposed control techniques. It is expected that the outcome of this research will provide a systematic procedure for the development of adaptive control and optimization. This could be utilized in a wide range of welding automation tasks such as developing intelligent control schemes for welding robots, developing a real-time monitoring and control system for the automated welding process, and providing state-of-the-art training facilities in the welding field, etc. Moreover, the scientific findings resulting from this research would also enhance the basic understanding and technical capabilities in the areas of control and automation. More importantly, it would lay the groundwork for promoting various ongoing and future interdisciplinary research activities relating to both education and industrial consultancies, such as the in-company training programs for the local industry on modern welding strategies and automation, the automation of other welding procedures, e.g. TIG and laser welding, and the development of customized research-oriented equipment for related academic and industrial use.

1.2. Background on Optimization Technics in Welding

1.2.1. Model-based optimization

Model-based optimization in welding involves using mathematical models to simulate and refine welding processes, incorporating equations that represent the physical phenomena present during welding, such as heat transfer, fluid flow, and metallurgical changes. These computational models are created to emulate welding behaviour under different conditions, forecasting results for various parameter combinations to pinpoint optimal configurations for desired weld attributes. This method fosters a systematic comprehension of the complex interplay between welding parameters and their impact on weld quality, enabling thorough exploration of different process variables and scenarios without extensive experimentation. Nonetheless, challenges emerge in crafting accurate and computationally efficient models, necessitating a profound understanding of welding physics and intricate numerical algorithms. Furthermore, disparities between simulation outcomes and real-world results may arise due to the inability to fully encapsulate the intricacies of actual welding processes [10].

The primary distinction between model-based and other forms of machine learning lies in the learning process's reliance on interactions between the agent and its environment. Consequently, the agent acquires task-specific knowledge directly from the environment without external instruction. However, delineating between the agent and the environment is not always straightforward and is contingent on the application [11]. For instance, in tasks like bipedal walking and UAV control, the environment is presumed to encompass the robot's motors.

In model-based methods, a model of transition dynamics is employed to derive rewards and optimal actions, with policies optimized within the model and subsequently applied to the physical system. Fig. 1 illustrates the model-based reinforcement learning pipeline.

1.2.2. Genetic Algorithms (GAs)

GAs represent an optimization technique inspired by natural selection and evolution, where a population of potential solutions evolves

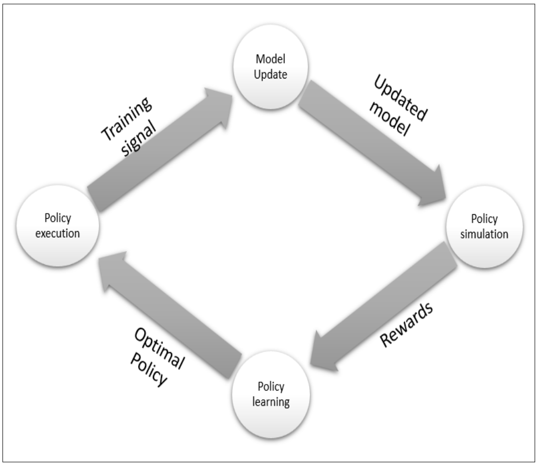

Fig. 1. *Model-based reinforcement learning pipeline.*

through successive generations via processes like selection, crossover, and mutation, with the fittest individuals selected for further reproduction. In welding, GAs are employed to optimize welding parameters by encoding them as chromosomes within a population. Through iterative generations, the algorithm evaluates the fitness of each solution, based on predefined objective functions such as weld quality metrics, selecting the best-performing individuals for subsequent generations. GAs offer a robust approach capable of handling complex, nonlinear optimization problems with multiple objectives and constraints, efficiently exploring large solution spaces and identifying near-optimal solutions in relatively short timeframes. However, effective utilization of GAs demands careful parameter tuning and selection of appropriate genetic operators to ensure convergence to meaningful solutions, while computational complexity may become prohibitive for highly dimensional optimization problems or computationally intensive welding models [12].

1.2.3. Particle Swarm Optimization (PSO)

The concept of PSO is derived from the collective behaviour observed in organisms like birds flocking or fish schooling, serving as a population-based stochastic optimization technique. In PSO, a group of potential solutions, depicted as particles, continually adjust their positions within the search space based on both individual experiences and shared knowledge within the swarm. Each particle embodies a potential solution encompassing a set of welding parameters, and its movement is guided by its personal best-known position as well as the collective best-known position uncovered by the swarm. Through this iterative process, the swarm progressively converges towards promising areas within the solution space, rendering PSO particularly advantageous for tasks characterized by continuous solution spaces and smooth objective functions. Despite its relative ease of implementation and computational efficiency, PSO's effectiveness may be influenced by the careful selection of control parameters, and it may encounter difficulties escaping local optima in intricate, multimodal optimization scenarios [13].

1.3. Adaptive control in Welding

Adaptive control strategies in welding represent a dynamic approach to optimizing welding processes by continuously adjusting control parameters in response to real-time feedback from sensors and environmental conditions. These strategies are designed to enable welding robots to adapt swiftly to changes in workpiece geometry, material properties, and other factors affecting the welding process, thereby enhancing overall process stability and robustness. Through the constant monitoring of critical process variables such as arc voltage, welding current, and torch orientation, adaptive control systems can effectively compensate for disturbances and variations encountered during welding operations [9]. This adaptability ensures that the welding parameters remain optimized for the specific conditions at hand, leading to improved weld quality and productivity. Furthermore, the integration of machine learning methods and advanced sensing technologies like vision systems and thermal imaging cameras further enhances the adaptability and precision of adaptive control systems by providing comprehensive feedback on the welding environment. Overall, adaptive control strategies represent a crucial advancement in welding technology, offering the potential to achieve consistently high-quality welds while maximizing efficiency and minimizing defects in diverse operating conditions [8].

Moreover, it is pivotal in optimizing the interaction between humans and welding robots, particularly in collaborative robotics or cobotics scenarios. In such setups, where humans and robots work together in shared spaces, adaptive control strategies are essential for ensuring safe and efficient collaboration. These strategies involve dynamically adjusting the robot's behaviour based on real-time feedback from sensors monitoring the human operator's movements, intentions, and safety. For instance, adaptive control systems can modulate the robot's speed, trajectory, and force exertion to prevent collisions or accidents, thus ensuring the safety of the human operator. Moreover, adaptive control allows the robot to adapt its behaviour to accommodate variations in the human operator's actions, preferences, and capabilities, enhancing the overall collaboration experience [8]. By continuously monitoring and analyzing the interaction between the human and welding robot, adaptive control systems can optimize task execution, minimize errors, and maximize productivity. Additionally, adaptive control enables seamless switching between autonomous robot operation and collaborative modes, providing flexibility and versatility in various welding applications [9]. Overall, the use of adaptive control in optimizing human-robot interaction in welding environments not only enhances safety and efficiency but also fosters a more intuitive and harmonious working relationship between humans and robots. Fig. 2 illustrates the steps of controlling the welding robot to ensure not only human safety but also the quality of the production.

2. Conclusions

The current state of welding technology lacks extensive integration of advanced algorithms for optimizing parameters and identifying defects, which is evident from limited accessible information. However, recent advancements have shown promising progress in utilizing neural networks to automate these processes, albeit in their early stages [5].

The application of machine learning in welding shows significant potential for progress, though further research and development are needed before implementation in industrial settings. Integrating machine learning into welding systems presents a valuable opportunity for advancement, offering improved parameter optimization and defect detection with greater precision and efficiency through the use of neural networks and other sophisticated algorithms. This automation potential could enhance productivity, and weld quality, and reduce reliance on manual adjustments and human inspection. Nevertheless, incorporating advanced algorithms into industrial welding will require considerable time and resources, with challenges such as data availability, algorithm robustness, and computational requirements needing to be addressed for reliable implementation.

Looking ahead, the future of intelligent welding systems depends on the continued exploration and advancement of machine-learning approaches. With further research, more tailored algorithms specifically designed for welding processes can be developed, enabling not only automated parameter optimization and defect detection but also real-time decision-making, adaptive control, and seamless integration into existing welding infrastructure.

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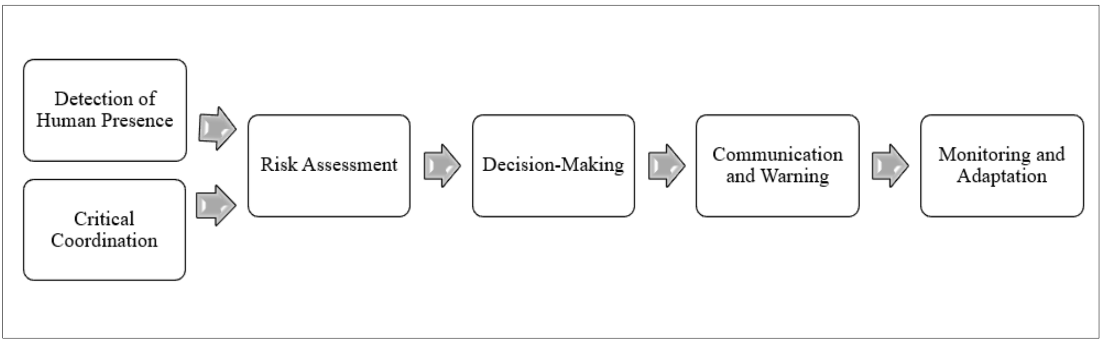

Fig. 2. *Safety and quality maintaining steps in welding robot controlling.*

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