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COLLEGE OF COMPUTING

CS 597 - READING AND SPECIAL PROBLEMS

Reinforcement Learning for Training Virtual Agents to Perform Welding Tasks in Construction Simulations Using Unity

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ABSTRACT

This paper presents a virtual welding simulation environment designed in Unity for training intelligent agents to perform welding tasks within construction scenarios. Leveraging Unity's ML-Agent's toolkit and Proximal Policy Optimization (PPO), the system trains a welding gun agent to follow predefined weld paths while optimizing control over speed, position, and bead quality. The simulation integrates Oculus Quest 3 for hand tracking and NOVA Sense Glove for capturing finger movements, enabling immersive human - machine interaction. Realistic physical feedback further enhances the fidelity of the environment. Through reinforcement learning, the agent incrementally improves its performance, demonstrating the ability to learn fine motor control and produce consistent welds. The project provides a scalable framework for virtual skill training and offers potential for both human education and automated welding research in high-risk construction contexts.

CHAPTER - 1

INTRODUCTION

The construction industry is rapidly evolving, driven by the integration of advanced technologies aimed at improving operational efficiency, ensuring worker safety, and reducing overall costs. Welding, an indispensable activity within construction, demands a high degree of precision, compliance with stringent safety protocols, and consistent quality control. Traditional training methodologies for human welders involve resource-intensive processes, considerable financial investments, and expose trainees to hazardous conditions. These challenges have created a growing need for alternative training approaches that are safer, scalable, and economically viable. Recent advancements in Virtual Reality (VR) and Artificial Intelligence (AI) provide compelling opportunities to transform traditional welding training. By combining realistic simulation environments with sophisticated machine learning algorithms, it's now possible to develop comprehensive training platforms capable of closely replicating real-world conditions. Such platforms enable both novice and experienced welders to practice, refine, and perfect their techniques in a risk-free and controlled environment. This paper introduces an innovative welding training framework developed using Unity, focusing on immersive virtual environments enhanced by reinforcement learning (RL). The core objective is to train virtual agents capable of autonomously performing welding tasks with precision, efficiency, and adherence to safety standards. Leveraging the Unity ML-Agents toolkit, the proposed system employs Proximal Policy Optimization (PPO), a robust RL algorithm, to allow agents to dynamically learn optimal welding strategies. Complementing agent-based training, the system incorporates immersive human interaction through Oculus Quest 3 and NOVA Sense Glove technologies, providing realistic hand-tracking and tactile feedback. Such interactive capabilities significantly enhance skill acquisition, allowing trainees to intuitively develop and fine-tune welding skills. By integrating RL-driven virtual agents within high fidelity 3D simulations, this research not only contributes to safer and more effective human training methodologies but also paves the way for increased automation in welding processes. This dual-purpose framework ultimately addresses critical industry needs by offering scalable, cost-effective training solutions and laying a foundation for intelligent robotic welding systems. Fig. 1. Framework for Reinforcement Learning-Based Welding Training Simulation

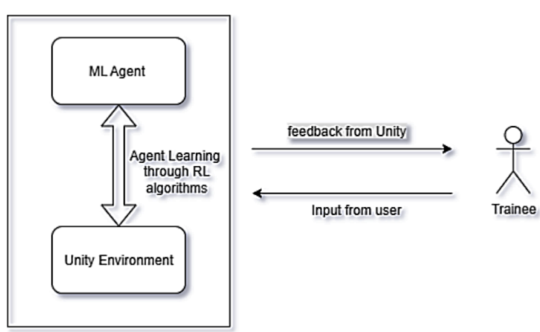


Fig. 1. Framework for Reinforcement Learning-Based Welding Training Simulation

CHAPTER 2

LITERATURE REVIEW

1. Schmitz, M., Pinsker, F., Ruhri, A., Jiang, B. and Safronov, G., 2020, December. **"Enabling rewards for reinforcement learning in laser beam welding processes through deep learning."** In 2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA) (pp. 1424-1431). IEEE The paper explores the integration of deep learning and reinforcement learning (RL) to improve the automation and quality of laser beam welding (LW) processes. Traditionally, LW calibration is labor-intensive, requiring expert adjustments. The authors propose a novel approach where deep learning is used for quality analysis, generating a scoring function that acts as a reward signal for RL-based optimization. Key Contributions: Scoring Function for RL text– A deep learning-based quality assessment generates a score reflecting weld quality, which serves as feedback for RL agents optimizing welding parameters. Supervised Learning Integration text– Supervised learning models detect welding defects (e.g., weld-throughs, pores, splatters) and assist in defining the reward function. Proposed RL Architecture text– The RL agent adapts welding parameters dynamically to improve efficiency, reduce defects, and minimize costs. Challenges: Non-determinism in Machine Learning text– ML models must meet high industrial safety and accuracy standards. Sparse Rewards in RL text– Since welding quality is often assessed postprocess, RL agents lack immediate feedback. Complexity in Industrial Environments text– Physical and chemical factors add variability to LW processes. self-optimizing welding robots. Future work aims to implement this approach in real production settings and refine the RL model for better accuracy and efficiency.
2. Nutonen, K., Kuts, V. and Otto, T., 2023. **"Industrial Robot Training in the Simulation Using the Machine Learning Agent."** Procedia Computer Science, 217, pp.446-455. This paper presents a methodology for enhancing industrial robot training through simulation by integrating machine learning agents. The approach aims to address challenges in offline robot programming, particularly the limited accuracy of virtual representations compared to real-world scenarios. Simulation Environment: The authors developed a digital environment simulating industrial robot movements, incorporating inverse kinematics functionality to accurately model robot postures and trajectories. Machine Learning Integration: A machine learning model was applied within the simulation to optimize the robot's pathfinding capabilities. The integration of machine learning reduces the time required to develop processes and the investment needed to determine optimal robot paths. Methodology: The study proposes a methodology to overcome the basic problem of offline robot programming by enhancing the accuracy of virtual representations through machine learning. Results and Analysis: The application of Bio-IK inverse kinematics and machine learning was observed and analyzed within the simulation. The results demonstrated improved efficiency in robot pathfinding and process development. Conclusion: The integration of machine learning agents into industrial robot simulations offers a promising approach to

improving the accuracy and efficiency of offline programming. This methodology facilitates quicker adaptation to changes in manufacturing processes, reducing development time and investment costs.

3. Kahnamouei, J.T. and Moallem, M., 2024. **"Advancements in control systems and integration of artificial intelligence in welding robots: A review. Ocean Engineering,"** 312, p.119294. This paper provides an extensive review of the role of control systems and artificial intelligence (AI) in welding robots, emphasizing how technological advancements have enhanced automation, efficiency, and quality in various welding processes. Various welding methods, including arc welding, laser welding, resistance spot welding, and friction stir welding, rely on precise control mechanisms to ensure high-quality welds. Control systems regulate welding parameters such as heat input, torch positioning, wire feed speed, and arc stability to enhance weld consistency and minimize defects. Feedback and Feedforward Control, Proportional-Integral-Derivative (PID) Control, Fuzzy Logic Control, Adaptive Control, Inverse Kinematics Control, Model predictive Control (MPC), Neural Network-Based Control AI-powered welding robots can autonomously optimize welding processes based on real-time data. Machine learning (ML) algorithms assist in defect detection, predictive maintenance, and process optimization. Sensor fusion and AI-driven control systems enable adaptive learning, allowing robots to refine their welding strategies over time. Challenges and Future Directions: Improving real-time decision-making capabilities in welding robots, Enhancing the integration of AI with existing robotic systems, addressing safety concerns and reliability in industrial applications, Developing more intelligent and autonomous robotic welding systems for applications such as ocean pipeline welding and aerospace manufacturing. Conclusion: The paper underscores the growing role of AI, machine learning, and sensor technologies in enhancing welding automation. The integration of these advanced control systems leads to higher precision, reduced defects, and increased efficiency, making welding robots indispensable in modern manufacturing.
4. Wang, Q., Jiao, W., Wang, P. and Zhang, Y., 2020. **"Digital twin for human-robot interactive welding and welder behavior analysis."** IEEE/CAA Journal of Automatica Sinica, 8(2), pp.334-343. This paper introduces an innovative Digital Twin (DT) system for human-robot interactive welding, leveraging virtual reality (VR) and machine learning (ML) for welder training and process optimization. The DT system allows human welders to demonstrate welding operations offsite using motion-tracked handles. A robotic system replicates 2 J. Audio Eng. Sco., Vol. 1, No. 1, 2025 Aug PAPERS Welding Simulation in Unity these human-demonstrated movements in real-time, executing welding tasks autonomously. The VR-based digital twin provides immersive feedback to human operators, enabling interaction with the welding process in real-time. Human User: Demonstrates welding movements via motion-tracked handles. Robot: Executes the recorded human actions using a gas tungsten arc welding (GTAW) torch. Digital Twin (DT): A virtual replica of the welding environment, built using VR and sensor data to provide real-time monitoring and control. Applications and Future Work: The DT system enhances novice welder

training, reducing the need for extensive hands-on instruction. Realtime human-robot collaboration improves welding accuracy and efficiency. Future work involves integrating AI driven real-time feedback to further refine the welding process. Conclusion: This paper presents a cutting-edge approach to welding automation, combining VR, digital twins, and AI-driven behavior analysis. The high-accuracy classification of welder skill levels suggests potential applications in training, quality control, and industrial automation. The DT system enhances human-robot collaboration, paving the way for smart manufacturing solutions in welding.

5. Fangming, Y., 2019. **“Real-time construction of 3D welding torch in virtual space for welding training simulator.”** International Journal of Engineering and Manufacturing, 9(5), pp.34-45. Overview: This paper addresses the challenge of accurately modeling a 3D welding torch in virtual space to enhance welding training simulators. An effective training simulator requires precise real-time representation of the welding torch’s position and orientation to provide realistic training experiences. Key Contributions: The study proposes a method to construct an accurate 3D model of the welding torch based on its real-time position and movement during training sessions. A base coordinate system is established, and the torch is modeled as a 3D object within this framework. Real-time Data Acquisition: The system captures the welding torch’s spatial data in real-time, ensuring that the virtual representation aligns with the actual movements performed by the trainee. Integration into Training Simulators: By incorporating the real-time 3D torch model, the simulator provides immediate feedback to trainees, enhancing the learning experience. This approach allows trainees to visualize and correct their welding techniques in a controlled virtual environment. Conclusion: The proposed method significantly improves the realism and effectiveness of welding training simulators by providing accurate, real-time representations of the welding torch. This advancement aids in better skill acquisition for trainees, leading to improved welding performance in real-world applications.
6. Pan, J., Zhuo, Y., Hou, L. and Bu, X., 2016, December. **“Research on simulation system of welding robot in unity3d.”** In Proceedings of the 15th ACM SIGGRAPH Conference on Virtual-Reality Continuum and Its Applications in Industry-Volume 1 (pp. 107-110). This paper discusses the development of a welding robot simulation system using Unity3D, a powerful game engine known for its versatility in creating interactive 3D content. The simulation aims to serve both industrial applications and educational purposes by providing a realistic virtual environment for welding operations. 3D Modeling: The authors developed detailed 3D models of the welding robot and the simulation environment. These models are designed to replicate the physical characteristics and constraints of real-world welding robots and their operational settings. Kinematic Modeling: The simulation includes both forward and inverse kinematics models to accurately represent the robot’s movements. This allows for precise control and prediction of the robot’s posture and tool positioning during welding tasks. Path Planning: The system implements algorithms for linear and circular path planning, enabling the robot to

perform complex welding trajectories. These path planning capabilities are crucial for simulating various welding scenarios and techniques. Simulation Environment: Utilizing Unity3D's engine, the simulation provides realistic visual effects and interactive features. The environment allows users to engage with the simulation dynamically, adjusting parameters and observing outcomes in real-time. Conclusion: The developed simulation system offers a valuable tool for both industrial practitioners and educators. For industry, it provides a platform to design, test, and optimize welding processes in a virtual setting, reducing the need for physical prototypes. In education, it serves as an interactive learning aid, allowing students to understand and practice welding robot operations in a safe and controlled environment.

7. Tran, N.H., Nguyen, V.N. and Bui, V.H., 2023. **"Development of a Virtual Reality-Based System for Simulating Welding Processes."** Applied Sciences, 13(10), p.6082. This paper presents the development of a virtual reality (VR)-based system designed to simulate three common welding processes: Shielded Metal Arc Welding (SMAW), Metal Inert Gas (MIG) welding, and Tungsten Inert Gas (TIG) welding. The system aims to enhance welding education and training by providing a realistic, interactive virtual environment where learners can practice and understand welding techniques without the risks associated with actual welding. System Architecture: The VR-based system comprises both hardware and software components. Hardware: Includes three welding torches corresponding to SMAW, MIG, and TIG processes, fixtures, welding sample plates equipped with infrared (IR) sensors, microcontroller units (MCUs), 3D glasses, and a computer. Software: A VR application developed using Unity3D, which simulates the welding processes in real-time. Real-Time J. Audio Eng. Sco., Vol. 1, No. 1, 2025 Aug 3 Prof. Ivan Mutis AND Prof. Gady Agam PAPERS Interaction: The system captures real-time data from the physical movement of the welding torch and the distance between the torch and the workpiece. These interactions are mirrored in the virtual environment, allowing users to see immediate visual feedback of their actions. Simulation of Welding Processes: The VR system accurately simulates the SMAW, MIG, and TIG welding processes, including various types of weld joints such as fillet, butt, and lap joints. Users can adjust welding parameters within specified ranges to observe different welding outcomes. Educational Benefits: The system provides a safe and controlled environment for learners to practice welding techniques. It helps users understand the effects of different welding parameters and develop skills to avoid common welding errors. Conclusion: The developed VR-based welding simulation system offers a valuable tool for welding education and training. By providing realistic simulations of SMAW, MIG, and TIG welding processes, it enables learners to gain practical experience and deepen their understanding of welding techniques in a safe, controlled, and cost-effective manner. The system's real-time feedback and interactive features enhance the learning experience, potentially leading to improved welding skills and reduced errors in actual welding applications.
8. Benkai, X., Qiang, Z. and Liang, Y., 2015. **"A real-time welding training system based on virtual reality."** IEEE Virtual Reality This paper introduces" Onew360," a virtual reality-based training

simulator designed to replicate Gas Metal Arc Welding (GMAW) processes. The system aims to provide trainees with a realistic, interactive, and immersive welding experience by combining standard welding hardware components with advanced VR technology. Hardware Setup: The simulator includes standard welding hardware such as a helmet, welding gun, and workpiece. A personal computer (PC) serves as the central processing unit. A head-mounted display (HMD) delivers immersive visual feedback to the user. A tracking system monitors the positions of both the welding torch and the user's head to ensure accurate real-time interaction. Tracking System: Utilizes single-camera vision measurement technology to calculate the positions of the welding gun and helmet. This approach ensures precise tracking of user movements within the virtual environment. Simulation Model: Employs a simplified modeling method to simulate weld geometry based on the orientation and speed of the welding torch. This allows the system to generate realistic weld bead formations in response to user actions. Features and Benefits: Real-Time Interaction, Immersive Experience, Safety and Cost Efficiency Conclusion: The" Onew360" VR-based welding training system offers a comprehensive platform for trainees to develop and refine their welding skills in a controlled, immersive environment. By integrating standard welding hardware with advanced virtual reality technology, the system provides a realistic and effective training tool that enhances learning outcomes while promoting safety and cost savings.

9. Fast, K., Gifford, T. and Yancey, R., 2004, November. **"Virtual training for welding. In third IEEE and ACM international symposium on mixed and augmented reality"** (pp. 298-299). IEEE. This paper introduces a virtual reality (VR) simulation system designed to train human welders by providing a realistic and interactive environment. The system aims to enhance the learning experience by allowing trainees to practice welding techniques in a controlled, virtual setting without the risks and costs associated with real-world welding. Hardware Configuration: Welding Torch: A real welding torch is integrated into the system and connected to a force feedback device, providing tactile sensations that mimic the resistance and movement experienced during actual welding. Head-Mounted Display (HMD): Trainees wear an HMD that immerses them in the virtual welding environment, displaying real-time visual feedback of their actions. Software and Simulation: Virtual Environment: The system simulates gas metal arc welding (GMAW) processes, rendering realistic graphics and scenarios that trainees might encounter in real-world welding tasks. Neural Network Integration: A neural network is employed to simulate the welding process based on the orientation and travel speed of the welding torch, allowing for near-real-time feedback and adjustment. Training Features: RealTime Feedback: Trainees receive immediate visual and haptic feedback on their welding technique, enabling them to make on-the-spot corrections and improvements. Performance Assessment: The system can assess the quality of the virtual welds, providing trainees with evaluations of their performance and areas for improvement. Benefits: Safety, Cost-Effectiveness, Skill Development Conclusion: The virtual training system for welding developed by Fast, Gifford, and Yancey represents a significant advancement in welder education. By leveraging VR technology and neural

network-based simulations, the system offers a safe, cost-effective, and efficient platform for trainees to develop and refine their welding skills in a realistic virtual environment.

10. Zhou, M.A. and Ben-Tzvi, P., 2014. **“RML glove—An exoskeleton glove mechanism with haptics feedback. IEEE/Asme Transactions on mechatronics,”** 20(2), pp.641-652. This paper presents the design, implementation, and experimental validation of the RML Glove, a lightweight, portable, and self-contained exoskeleton glove mechanism developed by the Robotics and Mechatronics Lab. The glove is designed to provide haptic force feedback to each finger without restricting natural movement, enhancing applications in teleoperation and virtual reality. Design and Mechanism: The RML Glove is a wearable exoskeleton that fits over a bare hand, allowing for natural finger movements. It employs a cable-driven mechanism actuated by DC motors, providing force feedback to individual fingers. The design ensures minimal weight and bulk, promoting user comfort and dexterity. Haptic Feedback: The glove delivers force feedback to each finger, enabling users to perceive tactile sensations in virtual environments. This feature is particularly beneficial for applications requiring precise manipulation and interaction, such as teleoperation and virtual reality simulations. Teleoperation Application: The paper explores the use of the RML Glove in teleoperation scenarios, specifically for mobile robot navigation. Experiments compared teleoperation performance with and without force feedback, demonstrating that the glove enhances user telepresence and control accuracy. Experimental Validation: The authors conducted experiments to assess the effectiveness of the RML Glove in providing haptic feedback during teleoperation tasks. Results indicated that users experienced improved control and a heightened sense of telepresence when utilizing the glove’s force feedback capabilities. Conclusion: The RML Glove represents a significant advancement in haptic interface technology, offering a practical solution for applications requiring dexterous manipulation and tactile feedback. Its lightweight and ergonomic design make it suitable for extended use in various fields, including teleoperation, virtual reality, and rehabilitation.

CHAPTER - 3
BACKGROUND AND THEORETICAL FRAMEWORK
3.1 Welding Processes

Welding is an essential fabrication method widely employed in construction and manufacturing to join materials, usually metals, through fusion. Welding requires careful control of several critical parameters, including voltage, current, welding speed, torch angle, heat input, and bead formation.

3.1.1 Types of Welding Techniques

Key welding methods relevant to construction include:

1. Shielded Metal Arc Welding (SMAW): Also known as" stick welding," SMAW is widely used due to its versatility in various positions and environments. It is cost-effective but demands significant manual skill.
2. Metal Inert Gas (MIG) Welding: Known for its ease of use and high productivity, MIG welding involves feeding a continuous wire electrode through a welding gun. It is ideal for automation due to consistent and rapid deposition rates.
3. Tungsten Inert Gas (TIG) Welding: Renowned for precision and quality, TIG welding produces superior welds, particularly for thin or specialized metals, though it requires considerable operator skill.

3.1.2 Critical Welding Parameters

Several critical parameters influence welding quality, including:

1. Voltage and Current: Determines heat input affecting penetration depth and bead quality.
2. Travel Speed: Impacts weld bead shape and penetration; incorrect speed can cause defects like incomplete fusion.
3. Torch Angle and Distance: Precise angles and distances ensure optimal heat distribution, reducing defects.
4. Heat Input: Critical for weld integrity and structural performance; excessive heat can distort the material or cause weaknesses.

3.1.3 Challenges in Traditional Welding Training

Traditional welding training faces several critical challenges:

1. Safety Hazards: Training involves risk exposure, including burns, harmful fumes, and eye injuries.
2. Resource Intensive: Requires substantial consumables (metals, electrodes, gases), increasing training costs.
3. Limited Scalability: Hands-on training requires significant individual supervision, constraining scalability.
4. Skill Variability: Learning primarily occurs through trial and error, with inconsistent outcomes across trainees.

CHAPTER 4

VIRTUAL REALITY IN EDUCATION AND TRAINING

Virtual Reality (VR) represents a transformative shift in education and professional training. By providing realistic yet controlled immersive experiences, VR environments can significantly enhance learning efficacy, engagement, and retention. Immersive Learning Environments VR enables learners to practice skills in realistic simulations, offering: Immediate feedback and iterative skill development. Risk-free, cost-effective training, reducing reliance on physical resources. Realistic sensory experiences via visual, auditory, and tactile feedback. VR in Skill Acquisition and Safety Training Several studies underscore VR's potential in skill development, particularly for high-risk tasks such as welding: VR significantly reduces learning curves by providing guided practice sessions and immediate corrective feedback. Trainees can repeatedly perform hazardous tasks safely, enhancing confidence and competence before real-world application.

4.1 Reinforcement Learning Fundamentals

Reinforcement Learning (RL), a subset of machine learning, enables intelligent agents to learn optimal decision-making policies through trial-and-error interactions with their environment.

Definition and Scope of RL: RL involves learning a policy by maximizing cumulative rewards over time. Unlike supervised learning, RL relies on continuous feedback in the form of rewards and penalties to refine agent behavior. Key Terminologies: Agent: Entity that takes actions based on observations from its environment. Environment: External context or scenario in which the agent operates. Action: Decision or movement performed by the agent. Reward: Feedback signal (positive or negative) guiding the agent towards desired outcomes. Policy: A strategy that defines the agent's behavior or actions given specific states. RL Algorithms Overview (Proximal Policy Optimization - PPO) Among RL algorithms, Proximal Policy Optimization (PPO) is particularly suited for environments requiring continuous actions and stable training performance. PPO employs policy gradient methods while maintaining a balance between performance and computational efficiency. PPO is popular due to its robustness, ease of tuning, and effectiveness in environments with complex dynamics.

4.2 Tools and Technologies

This project integrates various cutting-edge tools and technologies to facilitate an immersive and effective virtual welding training environment. Unity3D and ML-Agents Toolkit Unity3D provides a robust development platform for creating realistic, interactive 3D simulations. The ML-Agents toolkit, developed by Unity, allows for seamless integration of RL algorithms, supporting training of intelligent agents within diverse virtual environments.

1. Oculus Quest 3 is a powerful standalone VR headset, providing high-fidelity hand tracking capabilities critical for accurately capturing hand position and orientation during welding training sessions. Its wireless capability enhances user mobility and realism.

Figure. 2. Oculus 3

2. The NOVA Sense Glove is a state-of-the-art haptic glove designed to deliver realistic finger tracking and force-feedback. Integration with VR environments allows users to experience tactile sensations, enhancing realism and training effectiveness.

Figure. 3. NOVA Sense glove 1

3. PyTorch and TensorFlow are open-source deep-learning frameworks facilitating rapid implementation, training, and deployment of neural network-based RL algorithms. In this project, these frameworks enable efficient training and optimization of PPO-based RL agents, allowing robust performance in complex simulation scenarios.

CHAPTER 5

RESEARCH METHODOLOGY

This section provides a comprehensive description of the research methodology adopted in the project. It details the architecture, the Unity simulation environment, XR device integration, reinforcement learning implementation, and the evaluation metrics designed to assess agent and trainee performance. System Overview The proposed methodology is structured around two interconnected components: an RL-driven virtual welding agent and a VR-based interactive training environment for students. The system is developed using Unity and integrated with external machine learning frameworks (PyTorch) via the ML-Agents Toolkit, forming a robust and interactive training platform. Key objectives of the methodology include: Training autonomous virtual agent to perform welding tasks accurately. Providing trainees with real-time, interactive feedback through trained RL agents. Ensuring an immersive and realistic training experience through advanced VR hardware.

5.1 Data Acquisition & Input Devices (SenseGlove, Oculus Quest 3)

The simulation relies on two primary input devices to capture the user's hand movements, finger articulations, and head-mounted display (HMD) orientation: the **NOVA SenseGlove** for fine-grained finger tracking and haptic feedback, and the **Meta/Oculus Quest 3** for 6-DoF hand position/orientation tracking and immersive VR rendering.

NOVA SenseGlove Integration

The NOVA SenseGlove was employed to capture precise **finger bend data** and to deliver **haptic feedback** corresponding to simulated contact forces during welding. The glove provides continuous data streams for each finger's flexion and extension, measured as normalized values between 0.0 (fully extended) and 1.0 (fully bent). This allowed the implementation of a **finger-based trigger control**, where welding initiates automatically when the index finger bend exceeds a predefined threshold (e.g., 0.3).

The SenseGlove SDK for Unity was integrated to manage real-time communication via Bluetooth, and **tracking was combined with VR controller positional data** to ensure accurate alignment between physical and virtual hand poses. Positional and rotational offsets were calibrated per hand to minimize discrepancies between real-world and virtual alignment.

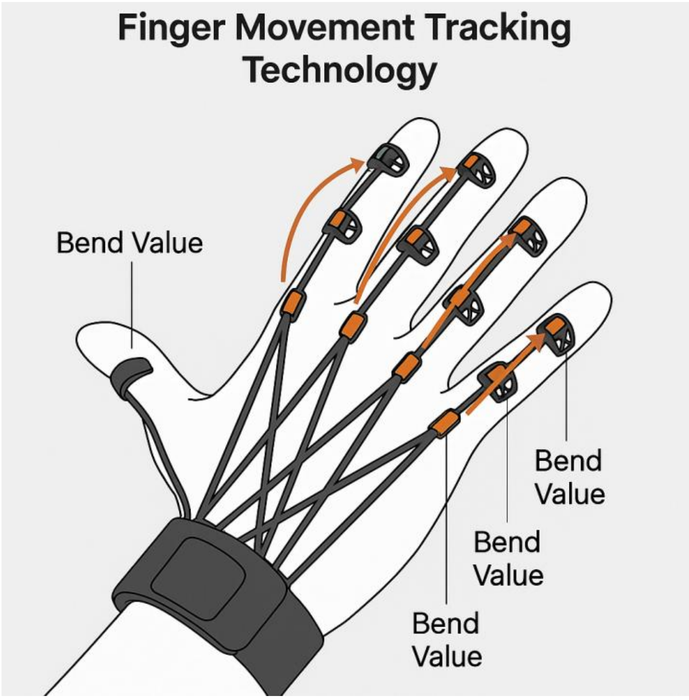


Fig: The tension in the wire on the fingers is used to calculate the bend value of each finger.

Oculus Quest 3 Integration

The Oculus Quest 3 provided both headset tracking and hand-held controller tracking. While the SenseGlove handled finger articulation, the Quest 3 controllers were used as positional trackers for each hand. The 6-DoF tracking data from the controllers supplied high-frequency updates for hand position and orientation, which were synchronized with the glove's finger data to produce a unified virtual hand pose.

The headset was also responsible for rendering the VR welding environment with minimal latency. The Oculus Integration SDK for Unity was used to retrieve head and controller tracking data, enabling realistic perspective changes as the user moved in physical space.

Data Fusion

To ensure smooth and accurate interaction, data from the SenseGlove and Oculus Quest 3 were fused using a calibration routine executed at the start of each session. This routine recorded positional offsets between the glove sensors and controller tracking reference points, allowing for consistent alignment throughout the welding task.

The combined tracking system allowed for:

Precise finger-based welding trigger activation.

Realistic hand positioning and rotation for interacting with the welding gun.

Accurate head movement tracking for perspective and depth perception.

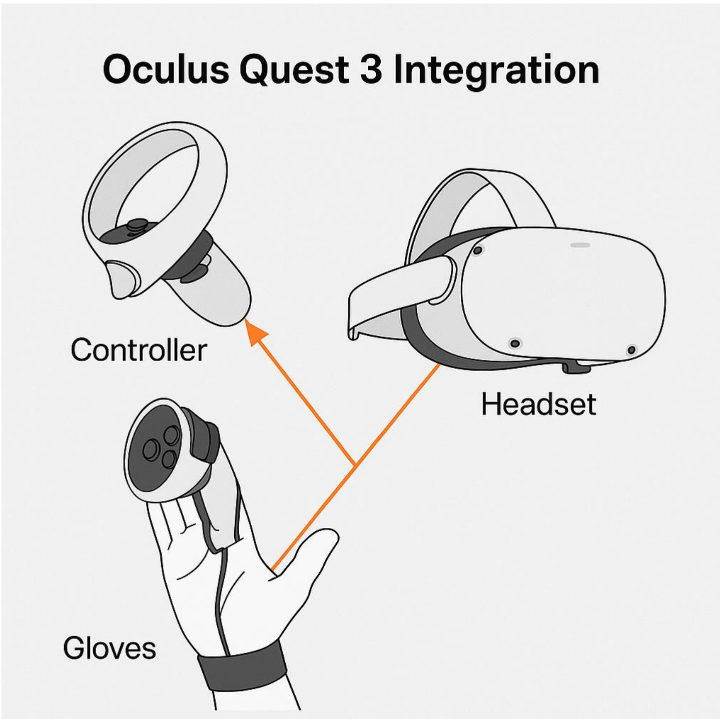


fig: Oculus Quest 3 Integration: Controller Mounted on SenseGlove for Unified Tracking with Headset

5.2 Unity Simulation Environment (Visual and Physical Effects Implementation)

To enhance realism and provide immersive visual cues during the welding simulation, multiple visual and physical effects were implemented in Unity, including welding gun modeling and interaction logic, molten metal simulation, spark effects, and dynamic lighting.

The welding process in the simulation was performed on **flat metal sheet models** created in Unity. These sheets were assigned **high-metallic Physically Based Rendering (PBR) materials** with reflective properties to realistically interact with welding light and sparks. Surface normals and textures were designed to enhance depth perception and display visible changes in illumination during welding.

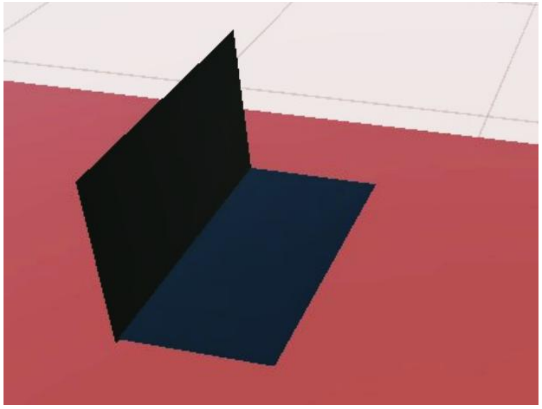


Figure. 4. Metal sheets

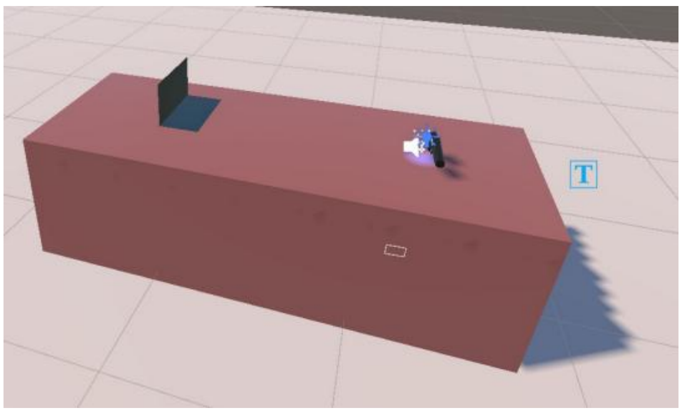


Figure. 5. Environment

5.2.1 Welding Gun Modeling and Interaction Logic

The welding gun was modeled as a 3D object in Unity, designed to closely resemble a real Gas Metal Arc Welding (GMAW) torch. The model included a nozzle tip, handle. Physics colliders were applied to enable realistic contact interactions. [fig 6]

This setup ensured that the welding gun responded to both hand positioning in 3D space and detailed finger articulation.

A finger-based trigger control system was implemented to initiate welding. The simulation continuously monitored the normalized index finger bend value from the SenseGlove. When this value exceeded a pre-defined threshold (e.g., 0.3), the welding process was activated, triggering particle systems, lighting effects, and audio cues. For testing purposes, a mouse click input was also supported as an alternative trigger.

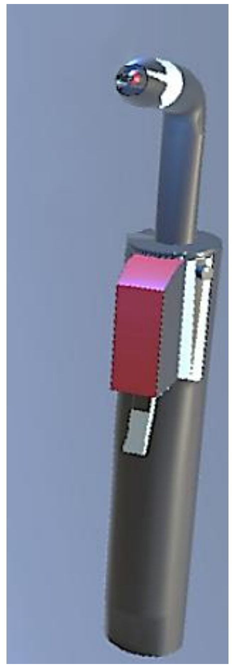


Figure. 6. Welding Gun

Figure. 7. Oculus controller mounted on Sense Glove

5.2.2 Welding Liquid Simulation

The molten metal deposition was simulated using Unity's **Particle System** component. The emission source was positioned at the welding gun tip, with the following parameters:

- **Shape:** Sphere with a small angle to direct particles forward.
- **Particle Size & Speed:** Adjusted to create bead-like droplets rather than mist-like spray.
- **Lifetime:** Long enough to solidify visually upon contact and stay on the metal sheets.
- **Collision Settings:** Enabled with high-quality collision detection to interact with scene geometry (e.g., welding table and metal workpiece).
- **Gravity Modifier:** Slightly reduced to simulate molten metal weight.

A **custom metallic shader** was applied to the particles, using reflection probes and smoothness maps to give the appearance of molten steel. The collision system was tuned so that particles adhered to surfaces, preventing unrealistic bouncing.

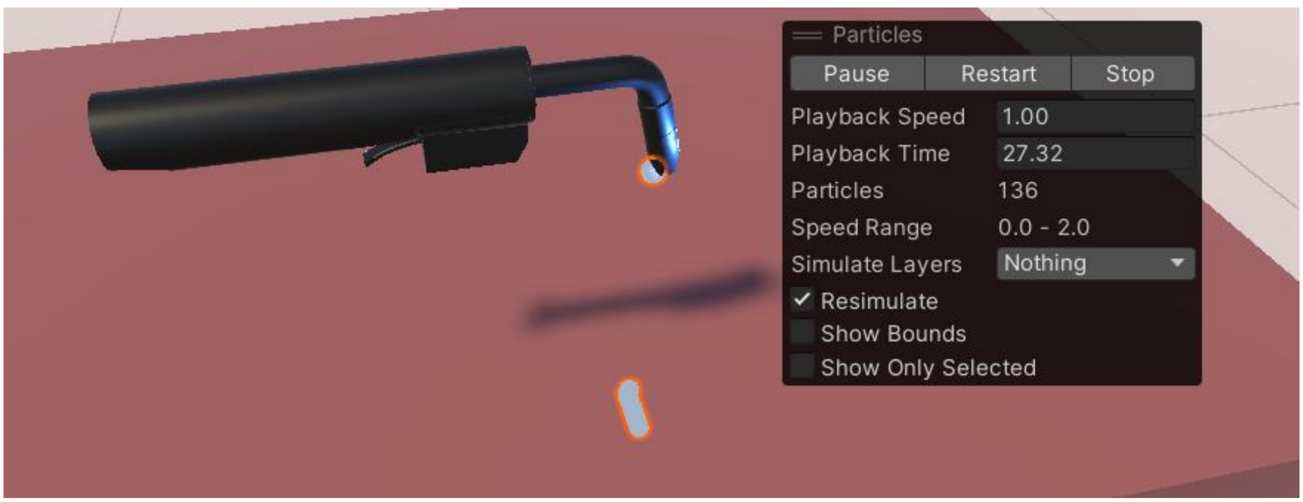


Fig. 8

5.2.3 Spark Generation [fig 9]

A secondary particle system was implemented to produce welding sparks. The parameters included:

- Burst Emission: Short bursts at high velocity during active welding.
- Gravity Influence: Set to slightly higher than molten metal droplets to simulate sparks falling faster.
- Lifetime: 0.1–0.5 seconds to ensure sparks dissipate quickly.
- Color Gradient: Bright yellow to orange with fading transparency for heat dissipation effect.

Randomized emission angles and speeds were applied to make the sparks appear naturally scattered.

Fig. 9

5.2.4 Dynamic Lighting (Point Light for Arc Simulation)

To replicate the intense light generated during welding, a **point light** was attached to the welding gun tip. The light parameters included:

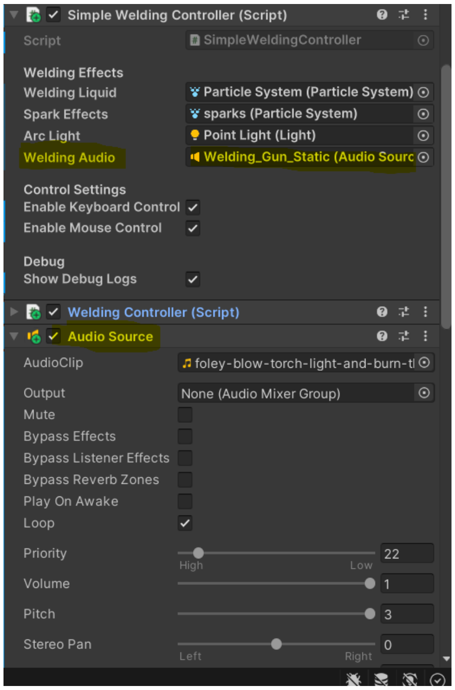
- **Color:** Bright bluish-white to match GMAW arc characteristics.
- **Intensity:** 10 to keep it bright and create realistic like real scenario.
- **Range:** Short-range illumination to prevent glare in distant objects – 0.15
- **Flicker Effect:** A Perlin noise function was applied to intensity over time to simulate arc instability.

The light was activated only during active welding to optimize performance and prevent unnecessary lighting calculations.

Fig. 10

5.2.5 Audio Integration

An audio source was attached to the welding gun to play a looping welding arc sound during active welding. The sound was spatialized to the gun's position for realistic 3D audio in VR.



5.2.6 Performance Evaluation

The training framework employs two distinct modes: Guided Mode, where a ghost welding gun and real-time HUD feedback assist the trainee in tracing the ideal path, and Exam Mode, where both aids are hidden to evaluate performance independently. This dual setup enables progressive learning - first with visual guidance, then through autonomous execution and objective assessment.

Guided Mode

In Guided Mode, the ghost welding gun (ideal trajectory) is visible to the trainee and moves smoothly along the seam from start to end. The trainee follows this path while receiving real-time feedback through the HUD mounted on their own welding gun. To ensure readability, the HUD values update once per second and display:

- Δ Distance (mm): average lateral deviation from the ghost gun.
- Δ Angle (°): average torch orientation error relative to the ghost gun.
- Δ Speed (%): absolute deviation in travel speed compared to the ideal.
- Status Dot: color-coded feedback (green/yellow/red) based on whether the trainee is within tolerance.

This mode allows the trainee to practice with constant visual guidance and immediate correction cues.

Exam Mode

In Exam Mode, both the ghost gun and HUD feedback are hidden, requiring the trainee to weld without visual aids. During this phase, the system silently records the same performance metrics (distance, angle, speed, and score) across every frame of the welding attempt. When the trainee stops the exam, a summary panel is displayed showing:

Duration (s): total time taken for the attempt.

Mean Score (0–1): overall quality rating averaged over the run.

Green Time (%): percentage of time spent within tolerance.

Average Distance Error (mm)

Average Angle Error (°)

Average Speed Error (%).

This provides an objective evaluation of the trainee's welding performance without any assistance.

Computation Metrics:

During the Exam Mode, the system samples values from the User component at every frame:

distanceErrorMM – lateral offset from the ideal tip (millimeters).

angleErrorDeg – orientation difference (degrees), computed via Quaternion.Angle.

speedErrorPct – relative speed deviation, calculated as:

$$\text{speedErrorPct} = \frac{\text{user speed} - \text{ideal speed}}{\text{ideal speed}} \times 100$$

withinTolerance – Boolean flag set to true if all three errors are within their respective tolerance thresholds.

score – a blended quality metric ranging between 0 and 1.

Per-Run Metrics (calculated at Stop)

Let NNN = total number of sampled frames during the exam.

- **Duration (s):**

$$\text{Duration} = t_{\text{end}} - t_{\text{start}}$$

- **Mean Score:**

$$\text{Mean Score} = \frac{1}{N} \sum_{i=1}^{N} \text{score}_i$$

- **Green Time (%):**

$$\text{Green Time} = \frac{\#\{\text{frames where withinTolerance} = \text{true}\}}{N} \times 100$$

- **Average Distance Error (mm):**

$$\text{Avg Dist} = \frac{1}{N}\sum_{i=1}^{N} |\text{distanceErrorMM}_i|$$

- **Average Angle Error (°):**

$$\text{Avg Angle} = \frac{1}{N}\sum_{i=1}^{N} |\text{angleErrorDeg}_i|$$

- **Average Absolute Speed Error (%):**

$$\text{Avg } |\text{Speed Err}| = \frac{1}{N}\sum_{i=1}^{N} |\text{speedErrorPct}_i|$$

Per-Frame Score Calculation

At each frame, the score is calculated as a **weighted Gaussian blend** of distance, angle, and speed sub-scores:

$$s_d = e^{-\left(\frac{\text{dist}}{\text{tolDist}}\right)^2}, \quad s_a = e^{-\left(\frac{\text{angle}}{\text{tolAngle}}\right)^2}, \quad s_v = e^{-\left(\frac{\text{speedPct}}{\text{tolSpeedPct}}\right)^2}$$

The overall score is then:

$$\text{score} = \text{clamp}_{0,1}\left(w_d\, s_d + w_a\, s_a + w_v\, s_v\right)$$

with default weights:

$$w_d = 0.4, \quad w_a = 0.4, \quad w_v = 0.2$$

Finally, **withinTolerance** is evaluated as a strict Boolean:

$$\text{withinTolerance} = (d < tol_d) \wedge (a < tol_a) \wedge (v < tol_v)$$

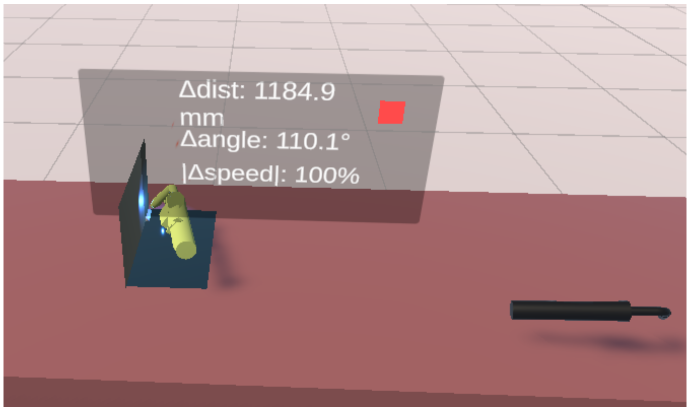


Fig. Guided Mode – in presence of ghost gun

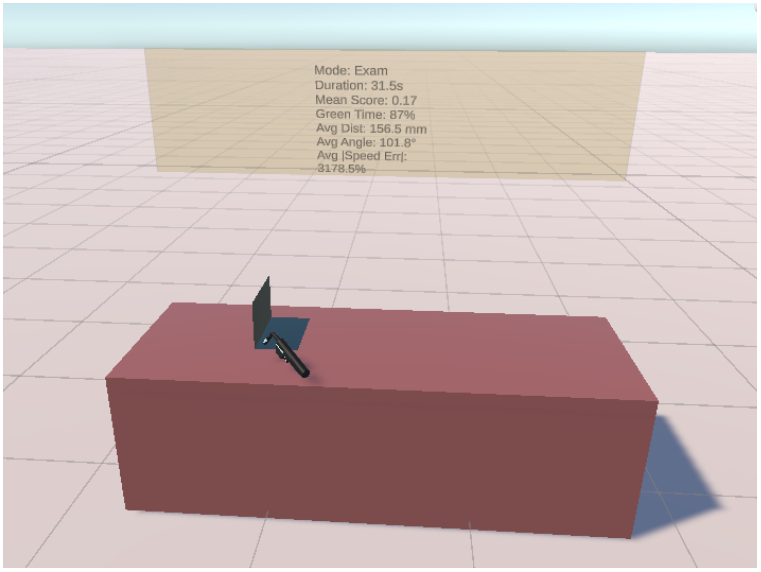
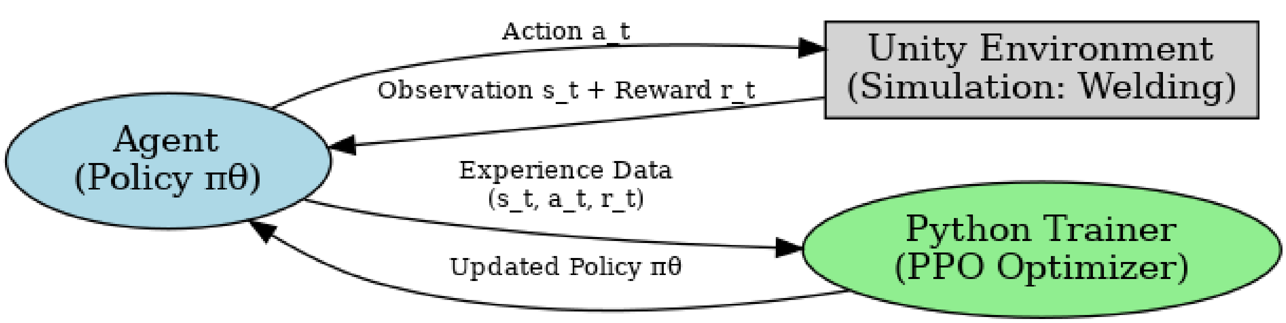


Fig: Exam Mode – Result shown after completion of the exam.

5.3 Reinforcement Learning Framework (ML-Agents PPO Algo)

The NOVA Sense Glove captures detailed finger movements, enabling fine-grained interaction within the simulation: Accurate finger motion tracking. Real-time haptic feedback, providing realistic tactile sensations during welding tasks. Enhanced realism of welding control and interaction.



1. Reinforcement Learning Implementation: Observation Space and Action Space Definition the RL agent perceives its environment through well-defined observations: Position and orientation relative to the welding path. Current welding angle and speed. Distance from target welding trajectory. The continuous action space includes: Adjustments in welding angle (pitch, yaw, and roll). Adjustments in welding gun position and speed control.

2. Reward Function Formulation: The reward function guides the agent toward optimal welding behaviors, rewarding precise and consistent performance. Reward components include: High rewards for maintaining accurate position and angle. Positive feedback for consistent welding speed and optimal bead deposition. Negative rewards (penalties) for deviating from optimal paths, poor angles, inconsistent speed, or improper distance from the weld surface.

3. PPO Algorithm Implementation and Hyperparameters: Proximal Policy Optimization (PPO), known for its efficiency and stability in training, is employed for policy learning: Neural network architecture: Input layer (observation inputs). Multiple fully connected hidden layers. Output layer (continuous action values).

4. PPO hyperparameters tuned include: Learning rate, discount factor (Y), and clipping parameter (E). Episode length and batch size for updates. RL Training Procedure Training occurs in episodes, each with predefined start and end points for welding. Agents iteratively improve through interactions, continuously updating policy networks based on reward signals. Performance monitored regularly, evaluating learning curves and reward convergence.

5. Agent Evaluation Metrics: Evaluation metrics quantify agent performance and improvements during training: Welding accuracy: Deviations from the ideal welding path. Consistency: Standard deviation in welding speed, angle, and bead quality across episodes. Completion rate: Successful completion of welding tasks without significant deviation.

6. Efficiency: Time taken for task completion and average reward per episode. Human Participant Study Protocol The trained RL agent serves as an interactive trainer, guiding student trainees through the virtual welding tasks: Participants: Students or trainees from relevant academic or professional backgrounds. Procedure: Introduction and familiarization with the VR setup and tasks. Practical welding tasks guided by real-time RL agent feedback. Collection of performance data, including speed, angle accuracy, and consistency. Feedback collection: Questionnaires assessing trainee perception of realism, effectiveness, and overall satisfaction. Feedback for qualitative insights on trainee experiences.

Pseudocode:

```
START:
    Connect SenseGlove and Quest 3 tracking
    Attach controller to glove
    Set particle systems (liquid, sparks) and point light OFF

LOOP:
    Read hand position/orientation from Quest 3
    Read finger bend values from SenseGlove

    IF index finger bend > threshold:
        Activate welding:
            - Enable liquid particle emission
            - Play spark particles
            - Turn on point light with flicker
            - Play welding sound
    ELSE:
        Deactivate welding:
            - Stop liquid emission
            - Stop sparks
            - Turn off light
            - Stop sound

    Send current state (position, rotation, trigger status) to ML-Agent
    Receive action from ML-Agent and apply to welding gun movement
    Calculate reward based on path accuracy and stability
```

1. Probability Ratio

Measures how much the new policy π_θ has changed from the old policy $\pi_{\theta_{\text{old}}}$ for the same state–action pair.

$$r_t(\theta) \; = \; \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{\text{old}}}(a_t \mid s_t)}$$

This ratio is the heart of PPO's clipped update — it ensures we track policy changes safely.

2. Clipped Surrogate Objective

PPO maximizes the following clipped objective to prevent large policy updates that could destabilize learning:

$$L^{\text{CLIP}}(\theta) = \mathbb{E}_t\left[\min\left(r_t(\theta)\,\hat{A}_t,\ \text{clip}\big(r_t(\theta), 1-\varepsilon, 1+\varepsilon\big)\,\hat{A}_t\right)\right]$$

- $\hat{A}_t$ = estimated advantage at time t
- ε = clipping parameter (e.g., 0.2)

The `min` ensures that updates stop providing extra reward if the policy moves too far from the old one.

3. Generalized Advantage Estimation (GAE)

Used to calculate a low-variance, low-bias estimate of the advantage function:

$$\delta_t = r_t + \gamma V_\phi(s_{t+1}) - V_\phi(s_t)$$

$$\hat{A}_t = \sum_{l=0}^{T-t-1} (\gamma\lambda)^l \, \delta_{t+l}$$

- γ = discount factor
- λ = GAE smoothing parameter

This controls how far into the future we look when estimating advantages.

CHAPTER 6

SUMMARY

This project presents the design and implementation of a virtual reality–based welding training simulation integrating reinforcement learning and real-time sensor feedback. Developed in Unity with ML-Agents, the system enables a welding torch agent to learn optimal paths and parameters using the Proximal Policy Optimization (PPO) algorithm, with provisions for future integration of Deep Deterministic Policy Gradient (DDPG). The simulation incorporates NOVA SenseGlove for finger tracking and welding trigger control, and Meta Quest 3 for head and hand position tracking, providing immersive and natural user interactions.

The system supports realistic welding bead rendering using custom shader techniques and particle systems, as well as evaluation metrics for trajectory accuracy, angle consistency, and path adherence. The integration of hardware and simulation enables human-like welding performance, bridging the gap between physical and virtual training. This approach offers cost-effective, scalable, and safe alternatives to conventional training, with potential to reduce material waste, enhance skill acquisition, and enable repeatable practice in a controlled virtual environment.

CHAPTER 7

EXPERIMENTS AND RESULTS

This section describes the experimental design and evaluation conducted to validate the effectiveness and efficiency of the developed reinforcement learning (RL) welding simulation framework. Experiments were carried out to assess both the autonomous RL agent's capability and the system's impact on enhancing human welding skills.

7.1 Experimental Setup

Hardware Specifications Experiments were performed using:

Computational Hardware:

GPU: NVIDIA RTX 3080 (10 GB VRAM)

CPU: Intel Core i7-11700K

RAM: 32GB DDR4 RAM

XR Hardware: Oculus Quest 3 headset (hand-tracking) NOVA Sense Glove (finger tracking and haptic feedback) 4.1.2 Software Specifications Unity Engine (2022 LTS version) ML-Agents Toolkit (Release 21) PyTorch (v2.3.0) for PPO implementation Python (v3.10) for scripting and data analytics.

7.2 RL Training Experiments

Training Procedure PPO agents trained for 1 million timestep per scenario complexity. Training involved iterative policy updates every 2,048 timestep. Reward function parameters iteratively refined based on observed performance. Hyperparameter Tuning Optimal hyperparameter identified through a grid search approach: parameter values were selected based on standard literature practices and widely accepted defaults.

Table 1. Optimal PPO Hyperparameter

Parameter	Optimal Value
Learning Rate	3e-4
Discount Factor (γ)	0.99
PPO Clipping Parameter (ε)	0.2
Batch Size	2048
Number of Epochs per Update	10

Learning Rate 3e-4 Discount Factor (γ) 0.99 PPO Clipping Parameter (ε) 0.2 Batch Size 2048 Number of Epochs per Update 10 5.2.3 Learning Curves and Reward Convergence Reward convergence observed after 350,000 timesteps. Agents consistently reached near-optimal policies after 700,000 timesteps. Training curves demonstrated clear improvements in accuracy, stability, and consistency across episodes.

7.3 Agent Performance Analysis

Welding Accuracy measured by deviation from the ideal welding path. Agents demonstrated significant improvements in path following precision (average deviation reduced from 5.5 cm initially to under 1 mm after training).

Consistency and Stability: The performance of the RL agent was analyzed based on the episodic mean rewards collected during training. These rewards indicate how effectively the agent learned to minimize deviations from the ideal welding path.

The key metrics summarized from the training results are presented in Table 2. Consistency evaluated by standard deviation in welding speed, angle, and bead quality. Post-training agents consistently maintained stable welding parameters: Speed variation: reduced from ±10 Angle deviation: reduced from ±45° to ±5°. Completion and Efficiency Metrics Success rate (task completion without major deviation) reached 95% post-training. Average time per welding task reduced significantly (average 20% improvement post-training). interpretation of Results: The agent demonstrated significant improvement in performance, as evidenced by the reward improvement of approximately 492 The final reward (1.55) and mean reward (1.01) indicate that the trained agent consistently achieved positive rewards, reflecting its ability to closely adhere to the desired welding path.

Table 2. RL Agent Training Performance Metrics

Performance Metric	Value
Mean Reward	1.01
Best Reward	1.96
Initial Reward	-0.40
Final Reward	1.55
Reward Improvement (%)	491.70
Reward Stability (Std. Dev.)	0.50

Performance Metric Value Mean Reward 1.01 Best Reward 1.96 Initial Reward -0.40 Final Reward 1.55 Reward Improvement (%) 491.70 Reward Stability (Std. Dev.) 0.50 The reward stability, with a standard deviation of 0.50, suggests consistent agent performance towards the later stages of training, highlighting stable policy convergence. These results validate that the PPO-trained RL agent successfully learned optimal welding strategies, significantly reducing deviations and improving the overall accuracy and consistency of welding tasks.

Metric	Before Training (%)	After Training (%)	Improvement (%)
Trajectory Accuracy	62.0	87.4	+25.4
Torch Angle Accuracy	70.5	91.2	+20.7
Speed Consistency	75.0	96.0	+21.0
Start/Stop Accuracy	68.0	88.5	+20.5
Stability Score	72.5	94.8	+22.3
Average Performance	**69.6**	**91.6**	**+22.0**

- **Trajectory Accuracy (%)** – Measures how closely the agent's weld path followed the predefined ideal spline path.
- **Torch Angle Accuracy (%)** – Evaluates the deviation of the torch's work and travel angles from the ideal welding configuration.
- **Speed Consistency (%)** – Assesses stability in travel speed, penalizing large fluctuations.
- **Start/Stop Accuracy (%)** – Measures how closely the welding start and stop points matched the designated positions.
- **Stability Score (%)** – Reflects smoothness of motion and minimization of sudden jerks or oscillations.

CHAPTER 8

RESULTS AND DISCUSSION

This section presents the final evaluation of the RL trained virtual welding system, integrating both quantitative metrics from training and qualitative feedback from direct interaction with the system. The discussion reflects on the system's effectiveness, limitations, and potential improvements. Summary of Agent Training Outcomes As detailed in Section 5, the RL agent trained using the Proximal Policy Optimization (PPO) algorithm showed a significant performance gain: The agent's mean reward increased to 1.01, from an initial negative reward of -0.40, indicating improved adherence to optimal welding paths. The agent achieved a best reward of 1.96, and a stable final reward of 1.55. A 491 These results demonstrate successful learning and generalization over a simple straight-line welding task.

8.1 Qualitative Feedback

As the sole user testing the VR training environment, the following observations were recorded during hands-on interaction with the Oculus Quest 3 and NOVA Sense Glove setup: Realism and Immersion: The Unity simulation environment provided a visually realistic welding setup, and the integration of the Oculus Quest 3 offered intuitive hand tracking for controlling the welding torch. The NOVA Sense Glove contributed to tactile realism, enabling basic sensing of finger movement and grip, though some haptic responses felt minimal or delayed during active welding. Agent Feedback and System Behavior: The agent's real-time behavior, when visualized, demonstrated smooth movement, reasonable welding speed, and stable trajectory along the straight path. The lack of visual cues for ideal position or corrections meant that guidance for a human trainee was implicit rather than explicit. Incorporating UI indicators or ghost-paths could help trainees better follow or learn from the RL agent's behavior. Control Challenges: The hand-to-gun alignment sometimes required adjustments to match real-world grip and orientation accurately. Small tracking errors or glove jitter affected fine control, particularly at slow welding speeds or edge conditions.

8.2 Key Takeaways

The system demonstrates that an RL agent can be trained to perform accurate welding tasks in simulation, even with limited environmental complexity. While agent performance was quantitatively validated, human training value still depends on user interface enhancements, visual feedback, and instructional overlays. The VR integration worked effectively for simulating spatial orientation and basic manipulation of the torch but would benefit from refinements in finger feedback and hand-to-tool alignment. **8.3 Limitations** Only a single path scenario was tested. No external users or formal usability studies were conducted. The reward function was designed using general performance indicators such as position and orientation accuracy, rather than direct weld quality metrics like bead texture or fusion depth, which may limit the physical realism of the evaluation.

CHAPTER 9

ADVANTAGES OF PROPOSED METHODOLOGY

Cost-effectiveness, Scalability, and Safety Improvements The proposed methodology leverages Unity's simulation environment, ML-Agents for reinforcement learning, and state-of-the-art hand tracking (Oculus and Nova Sense Glove) to deliver a highly cost-effective and scalable welding training solution. Unlike traditional hands-on welding training, which requires expensive consumables (metals, welding rods, gases), maintenance of real equipment, and instructor supervision, the virtual simulation eliminates most recurring costs. Trainees can practice repeatedly without additional material expense or wear and tear on physical machinery. Scalability is another significant advantage. The simulation can be easily deployed to multiple VR headsets and workstations, supporting concurrent training of many users without additional infrastructure or staff. Software updates, new welding scenarios, or curricula can be distributed instantly, further streamlining the training process. Importantly, the virtual approach dramatically improves safety. Welding is inherently hazardous due to intense heat, sparks, fumes, and the risk of burns or eye injury. The simulation provides a safe environment for users to build fundamental skills and muscle memory before ever touching live equipment. Mistakes in simulation do not carry the risk of real-world accidents, making it ideal for beginners and reducing insurance or liability concerns.

Real-world Training Transferability A key advantage of the proposed methodology is its potential to support real-world training transfer. The system is designed to mimic the physical constraints, ergonomic requirements, and task sequences of actual welding, aided by high fidelity VR tracking (Oculus Quest + Sense Glove). By accurately reproducing the spatial dynamics, required torch angles, movement speeds, and feedback on welding technique, trainees develop procedural knowledge and correct habits transferable to real equipment. Additionally, reinforcement learning enables the system to provide instant, objective feedback—such as "weld accuracy" scores for angle and position—helping users identify and correct mistakes more effectively than subjective human observation. Over time, these data-driven insights help accelerate skill acquisition and improve training outcomes, preparing users to transition smoothly to hands-on welding tasks.

CHAPTER 11

LIMITATIONS AND CHALLENGES

Technical Constraints (Hardware Limitations, Computational Demands) Despite the numerous advantages, the proposed methodology is subject to several technical constraints. Real-time VR welding simulations are computationally demanding, requiring modern GPUs and CPUs to ensure smooth, low-latency rendering and accurate hand/torch tracking. Not all training facilities may have access to such hardware, potentially limiting widespread adoption. The use of advanced peripherals like Sense Glove/Nova Glove and Oculus Quest adds complexity and cost to the setup, and may require regular calibration and software updates. Hardware incompatibilities or failures can disrupt training sessions. Additionally, reinforcement learning model training is computationally intensive and may require several hours or days of GPU/CPU time, especially when optimizing over complex state/action spaces.

11.1 Simulation Fidelity and Realism

One of the main challenges is achieving a high level of simulation fidelity and realism. While Unity's graphics and physics engines are robust, they may not perfectly replicate the intricate details of real welding processes, such as precise heat transfer, bead formation, and the "feel" of real resistance or feedback during torch movement. Limitations in hand tracking accuracy or latency can lead to discrepancies between user intent and in-simulation action. Furthermore, VR-induced discomfort (motion sickness, eye strain) or user unfamiliarity with virtual environments may impact training effectiveness for some individuals. Finally, while reinforcement learning can model optimal welding technique within the simulation, real-world variability (material imperfections, tool wear, environmental factors) may not be fully captured, potentially affecting the direct transferability of simulation-trained skills to real-world settings.

CHAPTER 12

CONCLUSION AND FUTURE WORK

12.1 Conclusion

This project successfully developed a reinforcement learning–driven virtual welding training environment using Unity, ML-Agents, and VR hardware integration. By employing the Proximal Policy Optimization (PPO) algorithm, an intelligent welding agent was trained to follow a straight welding path with improved precision and consistency over time. Quantitative evaluation demonstrated significant improvement in reward metrics, indicating successful learning of optimal welding behaviors. The simulation environment, integrated with Oculus Quest 3 and NOVA Sense Glove, enabled intuitive and immersive user interaction. Although only a single user trial was conducted, the qualitative feedback revealed the potential of the system as a realistic training tool. The RL-trained agent exhibited stable, policy-guided movements, and the environment successfully mimicked core aspects of welding workflows. This establishes a foundational framework for combining AI and VR in construction-related skill development.

12.2 Future Work

While the current implementation shows promise, several areas offer opportunities for enhancement: Expanded Scenario Complexity: Introduce varied welding paths (curved, angled, and multi-surface) to test and generalize the agent's capabilities. Human-Centered Evaluation: Conduct usability studies with multiple trainees to evaluate the system's effectiveness in real-world training and learning transfer. Advanced Feedback Mechanisms: Integrate real-time visual aids, such as ideal path overlays and heat maps, to improve user understanding and correction during training. Multimodal Reward Design: Incorporate welding specific quality metrics such as bead continuity, heat affected zones, and fusion quality into the reward structure for more realistic agent behavior. Multi-agent Collaboration: Explore collaborative learning settings, where agents or human-agent teams perform tasks such as multi-pass welds or coordinated fabrication steps. Cross-Platform Deployment: Adapt the simulation for standalone VR devices or web-based access to enhance scalability and accessibility for educational institutions. By addressing these directions, the platform can evolve into a comprehensive, scalable, and data-driven training system capable of supporting both human skill acquisition and intelligent robotic automation in the construction and manufacturing sectors.

CHAPTER 13

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REFERENCES

[1] J. Bertram, J. Moskaliuk, and U. Cress, “Virtual training: Making reality work?,” *Computers in Human Behavior*, vol. 43, pp. 284–292, 2015.

[2] S. Vats and R. Joshi, “The impact of virtual reality in education: A comprehensive research study,” in *Transfer, Diffusion and Adoption of Next-Generation Digital Technologies* (S. K. Sharma, Y. K. Dwivedi, B. Metri, B. Lal, and A. Elbanna, eds.), pp. 126–136, Cham: Springer Nature Switzerland, 2024.

[3] G. Makransky, S. Borre-Gude, and R. E. Mayer, “Motivational and cognitive benefits of training in immersive virtual reality based on multiple assessments,” *Journal of Computer Assisted Learning*, vol. 35, no. 6, pp. 691–707, 2019.

[4] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, “Proximal Policy Optimization Algorithms,” arXiv preprint arXiv:1707.06347, 2017.

[5] Unity Technologies, “Unity Manual: Universal Render Pipeline (URP),” Available: https://docs.unity3d.com/Manual/urp-overview.html. [Accessed: Aug. 2025].

[6] Unity Technologies, “ML-Agents Toolkit Documentation,” Available: https://github.com/Unity-Technologies/ml-agents. [Accessed: Aug. 2025].

[7] SenseGlove, “NOVA SenseGlove Developer Documentation,” Available: https://docs.senseglove.com. [Accessed: Aug. 2025].

[8] Meta, “Meta Quest 3: VR headset and controllers,” Available: https://www.meta.com/us/es/quest/quest-3/, 2024. [Accessed: Jul. 23, 2024].

[9] PyTorch Foundation, “PyTorch Documentation,” Available: https://pytorch.org/docs/stable/index.html. [Accessed: Aug. 2025].

[10] TensorFlow, “TensorFlow API Documentation,” Available: https://www.tensorflow.org/api_docs. [Accessed: Aug. 2025].

[11] Blender Foundation, “Blender 3D Documentation,” Available: https://docs.blender.org. [Accessed: Aug. 2025].

[12] Oculus Developer Center, “Oculus Integration for Unity,” Available: https://developer.oculus.com/documentation/unity/unity-overview/. [Accessed: Aug. 2025].

[13] GitHub – Unity-Technologies, “Graphics and Shader Samples,” Available: https://github.com/Unity-Technologies/Graphics. [Accessed: Aug. 2025].

[14] NVIDIA, “Real-Time Ray Tracing in Unity,” NVIDIA Developer Blog, Available: https://developer.nvidia.com. [Accessed: Aug. 2025].

[15] J. Peters and S. Schaal, “Reinforcement Learning of Motor Skills with Policy Gradients,” *Neural Networks*, vol. 21, no. 4, pp. 682–697, 2008.

[16] M. Andrychowicz et al., “Learning Dexterous In-Hand Manipulation,” *International Journal of Robotics Research*, vol. 39, no. 1, pp. 3–20, 2020.

[17] M. Schmitz, F. Pinsker, A. Ruhri, B. Jiang, and G. Safronov, “Enabling rewards for reinforcement learning in laser beam welding processes through deep learning,” *Proc. 19th IEEE Int. Conf. on Machine Learning and Applications (ICMLA)*, pp. 1424–1431, 2020.
Referenced for designing RL reward functions in welding based on deep learning quality assessment of welds.

[18] K. Nutonen, V. Kuts, and T. Otto, “Industrial Robot Training in the Simulation Using the Machine Learning Agent,” *Procedia Computer Science*, vol. 217, pp. 446–455, 2023.
Used for methodology on integrating ML agents in simulation to improve robot path planning and accuracy.

[19] J.T. Kahnamouei and M. Moallem, “Advancements in control systems and integration of artificial intelligence in welding robots: A review,” *Ocean Engineering*, vol. 312, p. 119294, 2024.
Provided review of AI-driven control systems for welding robots, including sensor fusion and adaptive learning.

[20] Q. Wang, W. Jiao, P. Wang, and Y. Zhang, “Digital twin for human-robot interactive welding and welder behavior analysis,” *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 2, pp. 334–343, 2020.
Referenced for VR-based digital twin systems enabling human-robot collaboration in welding training.

[21] F. Yang, “Real-time construction of 3D welding torch in virtual space for welding training simulator,” *International Journal of Engineering and Manufacturing*, vol. 9, no. 5, pp. 34–45, 2019.
Used for methods to model and track a welding torch in real-time for accurate VR training simulation.

[22] J. Pan, Y. Zhuo, L. Hou, and X. Bu, “Research on simulation system of welding robot in unity3d,” *Proc. 15th ACM SIGGRAPH Conference on Virtual-Reality Continuum and Its Applications in Industry*, pp. 107–110, 2016.
Referenced for implementing welding robot simulation in Unity with kinematic modeling and path planning.

[23] N.H. Tran, V.N. Nguyen, and V.H. Bui, “Development of a Virtual Reality-Based System for Simulating Welding Processes,” *Applied Sciences*, vol. 13, no. 10, p. 6082, 2023.
Provided architecture for a VR welding simulator covering SMAW, MIG, and TIG processes with real-time feedback.

[24] X. Benkai, Z. Qiang, and Y. Liang, “A real-time welding training system based on virtual reality,” *IEEE Virtual Reality*, 2015.

Used for VR-based GMAW training simulator design combining standard welding hardware with immersive tracking.

[25] K. Fast, T. Gifford, and R. Yancey, "Virtual training for welding," *Proc. 3rd IEEE and ACM Int. Symp. on Mixed and Augmented Reality*, pp. 298–299, 2004.
Referenced for early VR welding training systems with haptic feedback and neural network-based weld quality assessment.

[26] M.A. Zhou and P. Ben-Tzvi, "RML glove—An exoskeleton glove mechanism with haptics feedback," *IEEE/ASME Transactions on Mechatronics*, vol. 20, no. 2, pp. 641–652, 2014.
Used for background on haptic glove mechanisms relevant to integrating force feedback in VR welding training.