

SSC2025 Category/Theme: Manufacturing — Next-Gen Manufacturing

Application of Artificial Intelligence Integrated Robotics in the Democratization of Manufacturing

Jovan Hartono¹, Kenneth Y T Lim², and Parith Avasadanond¹

¹ Independent Scholar, Singapore

² National Institute of Education, Nanyang Technological University, Singapore

Keywords: Personalized manufacturing, Reinforcement learning, Artificial Intelligence, Robotics, Computer vision

Background

Robotics application in personal manufacturing has long been constrained by the problem of generalisation across diverse and unstructured environments. While reinforcement learning (RL) has provided significant advances in robotic control, its effectiveness is hindered by the simulation–reality gap and the difficulty of designing robust reward functions for multitask. Recent progress in large language models (LLMs) offers new opportunities for bridging symbolic reasoning and physical control, potentially enabling robots to adapt more flexibly to novel tasks. This work builds on the hypothesis that combining the semantic understanding of LLMs with the continuous control capacity of RL agents. This ultimately aims towards pushing general robotics technology to allow everyone to have access to manufacturing based on their specific use case, in light of the rise of the gig/freelance economy and e-commerce where labour in the manufacturing and assembling to packaging aspect is a major drawback and limitation to maximising creative growth and revenue. One of the hopes of this technology is to democratise personal manufacturing for the betterment of the people in the fields that benefit from this.

Objectives

The project seeks to 1. Enable natural language commands to be translated into executable robotic actions. 2. Train RL policies in simulated environments for transfer to real-world execution 3. Develop curriculum-based training pipelines where LLMs assist in environment design, object generation, and reward shaping. 4. Testing in personal/mesoscale and task specific manufacturing applications

Methodology

For proof-of-concept, an AR4-MK3 robotic arm from Annin Robotics was assembled and augmented with a Raspberry Pi 5 and AI kit, a Pi AI camera, Teensy 4.1 microcontroller, LiDAR, and audio I/O peripherals. Natural language commands are parsed by an LLM and converted into structured action primitives. A custom interpreter translates these into low-level motor control instructions, which are executed through pre-trained RL policies. Policies are initially trained in digital simulation platforms such as PyBullet and Isaac Gym, using various algorithms. The methodology also incorporates curriculum-based training, where the LLM

generates URDF objects, environment parameters, and candidate reward functions. The mathematical foundation of the system draws from linear algebra, probability theory, control systems, and calculus of variations.

Results and Discussion

Preliminary results suggest that the integration of LLM-driven semantic parsing with RL-based motor control offers a promising approach to task generalisation. Robotics reinforcement learning has demonstrated sim-to-real transferability through domain randomization [1], while recent benchmarks validate large-scale policy learning methods [2]. However, challenges remain. Firstly, compute resource constraints limit the scale of policy training, while errors in LLM-generated environments and reward functions introduce risks of error propagation. Furthermore, the transfer of policies from simulation to real hardware continues to expose discrepancies that reduce robustness. Despite these limitations, the hybrid architecture provides evidence that combining LLMs with RL can enable more adaptive, multimodal, and generalisable robotic systems than either approach alone.

Conclusions

This work demonstrates a novel integration of large language models and reinforcement learning agents within a robotic control pipeline. Future work will focus on scaling policy training, refining LLM-driven environment generation, and expanding the scope of multimodal interaction to further bridge the gap between symbolic intelligence and embodied control.

REFERENCES

- [1] J. Tobin, R. Fong, A. Ray, J. Schneider, W. Zaremba, and P. Abbeel, “Domain Randomization for Transferring Deep Neural Networks from Simulation to the Real World,” *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 23–30, 2017. doi: [10.1109/IROS.2017.8202133](https://doi.org/10.1109/IROS.2017.8202133).
- [2] S. Cobbe, J. Hilton, O. Klimov, and J. Schulman, “Leveraging Procedural Generation to Benchmark Reinforcement Learning,” *International Conference on Learning Representations (ICLR)*, 2020. Available: <https://openreview.net/forum?id=3R3Pz5i0tye>.