Comparative Evaluation of Vision-based kinematic Control and Imitation learning Approaches for Isotope Production Automation

Ricardo Carranza Jr, Dominic Motekaitis, Otmane Alami, Ravi Gampa, Jerry Nolen, Millicent Firestone, Yongho Kim
Argonne National Laboratory, Argonne, IL USA 60439

Advances in artificial intelligence and robotics have the potential to transform radioisotope production by enabling autonomous execution of routine laboratory procedures, reducing operator burden, and improving process reproducibility. As an initial demonstration, dissolution of an enriched solid isotope target was selected as the first unit operation because it is a common and essential step in radioisotope separation and purification workflows. Two autonomous control strategies were investigated: an imitation learning approach trained directly from expert demonstrations and a vision-based kinematic control method.

For the imitation learning framework, a teleoperation system and cameras were used to capture human demonstrations. After refining the data collection pipeline through adjustments to camera configuration and demonstration episode selection, the data were utilized to train an action chunking transformer (ACT) model with the LeRobot Python library that was developed by Hugging Face. The best-performing policy was selected through real-world trials, with success rate as the primary metric. For the kinematic control approach, images of flask and target configurations were collected and annotated, then divided into training and evaluation datasets for a YOLO-based object detection model. These detections were integrated into a kinematic control pipeline and evaluated through the same real-world trials. Both approaches were evaluated and benchmarked against human-operated trials to assess their ability to reproduce expert behavior and execute the task autonomously.

The imitation learning model achieved a 47% success rate, whereas the vision-based kinematic control approach achieved an 80% success rate. In more difficult trials, the vision-based kinematic control approach either successfully completed the task or came close to doing so, while the imitation learning model was less successful. These results suggest that, for this type of pick-and-place task, vision-based kinematic control is the better-performing strategy. It also required less training time and a more streamlined data collection process. However, this method depends on careful calibration, mapping image to physical workspace coordinates, and on maintaining a fixed camera configuration. Nevertheless, both strategies demonstrate the feasibility of leveraging expert teleoperation data to develop machine learning-guided robotic systems for radiochemical processing. The executed data collection framework and autonomous control strategies establish a foundation for future autonomous laboratory operations and represent an important step toward intelligent robotic systems capable of supporting next-generation isotope production.

This work was supported by the U.S. Department of Energy (DOE), Office of Science, through the Advanced Scientific Computing Research (ASCR) program and the Isotope Research and Production (IRP) program under the *Accelerate Innovations in Emerging Technologies* (AIET) DOE National Laboratory Program Announcement (LAB 23-3010). Support from ASCR enabled the development and application of machine learning methodologies for data-driven analysis of chromatographic separations, while support from IRP enabled the radiochemical studies and experimental validation of these approaches in the context of isotope production.