Semi-autonomous grasping for assisted glovebox operations

Authors: Erwin Lopez, Radhika Nath

Institutions: The University of Manchester, RACE

RAIN

Abstract

A semi-autonomous approach for robotic grasping inside a glovebox is presented, as control is shared between the robot's planning and control algorithms, and the user's validation and selection inputs. This approach aims to improve task performance and flexibility by relying on the user's flexible planning and the robot's precise task execution. Poor visibility, clutter and uncertainty of objects inside glovebox environments make handling items very challenging. We focus on cases where solid debris need to be cleared from an area. This can be dangerous and cumbersome when attempting manually, as they could include sharp and hazardous items. While autonomous grasping models supported by machine learning techniques can be applicable in these scenarios due to its efficiency and accuracy, certain safety critical operations may require human input. In the semi-autonomous grasping system, we take advantage of the intermediate outputs of the generative grasp models. By using the generated grasp probability as a 2D map, multiple grasp probabilities are presented to the operator through a user-friendly interface, which allows them to direct the robot towards the appropriate direction.

Semi-Autonomous grasp system

The semi-autonomous system (Figure 1) pairs a generative grasp convolutional network (GGCNN)[1] that produces grasp coordinates based on image input, with a Unity-based control interface (VR and Desktop). A digital twin representing the robot state is shown, together with sensor feed from the glovebox (i.e. cameras) and the GGCNN's grasp probabilities for graspable objects in the glovebox. External LED status indicators are used to communicate the state of the semi-autonomous system (Figure 3).

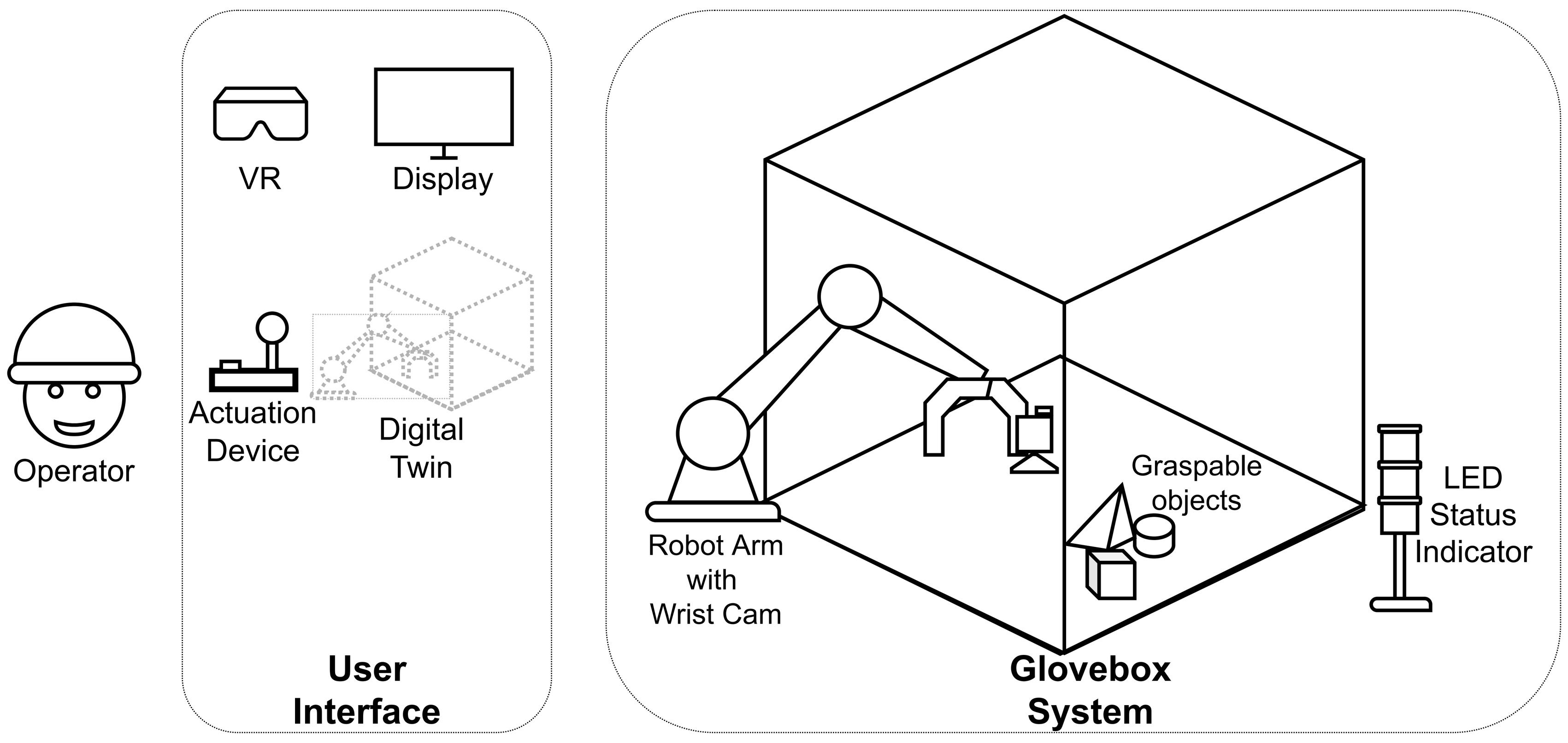

Figure 1: General system view of the semi-autonomous grasping system

The testing of grasp success rate is carried out with a set of adversarial objects like the Evolved Grasping Analysis dataset (Figure 2), which include various levels of shape complexity and grasp difficulty [2].

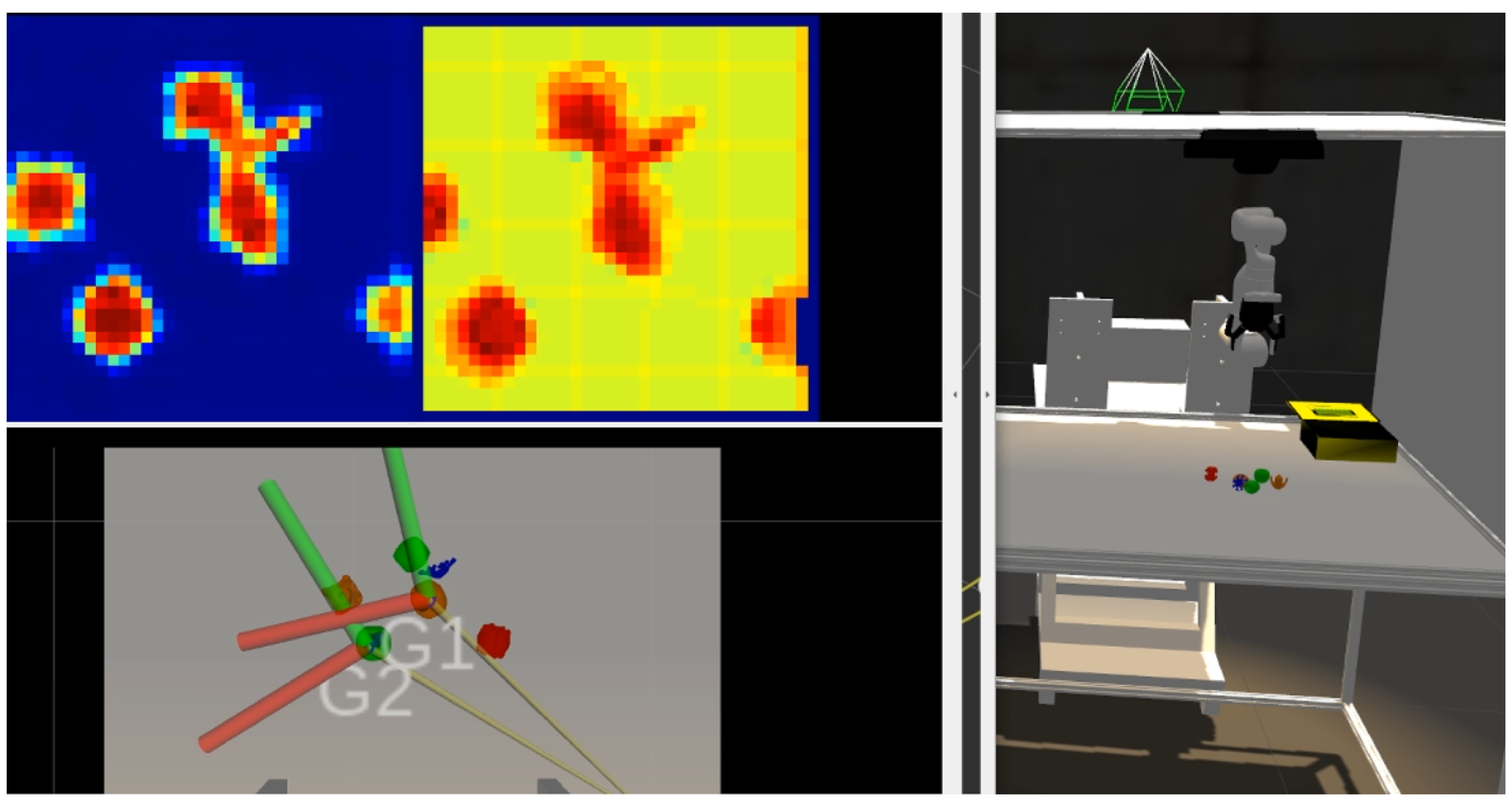

Figure 2: The grasp probability and grid map from the GGCNN for a random selection of EGAD objects. Multiple grasp candidates are also produced from the neural network

Execution Flow and User Interface

The execution flow (Figure 3) for the semi-autonomous system was taken from a linear automatic code execution designed for autonomous mode. User input was given to provide start and stop signals to be given by users, enabling to reset or reconfigure the system and allowing the user to avoid ambiguous task execution.

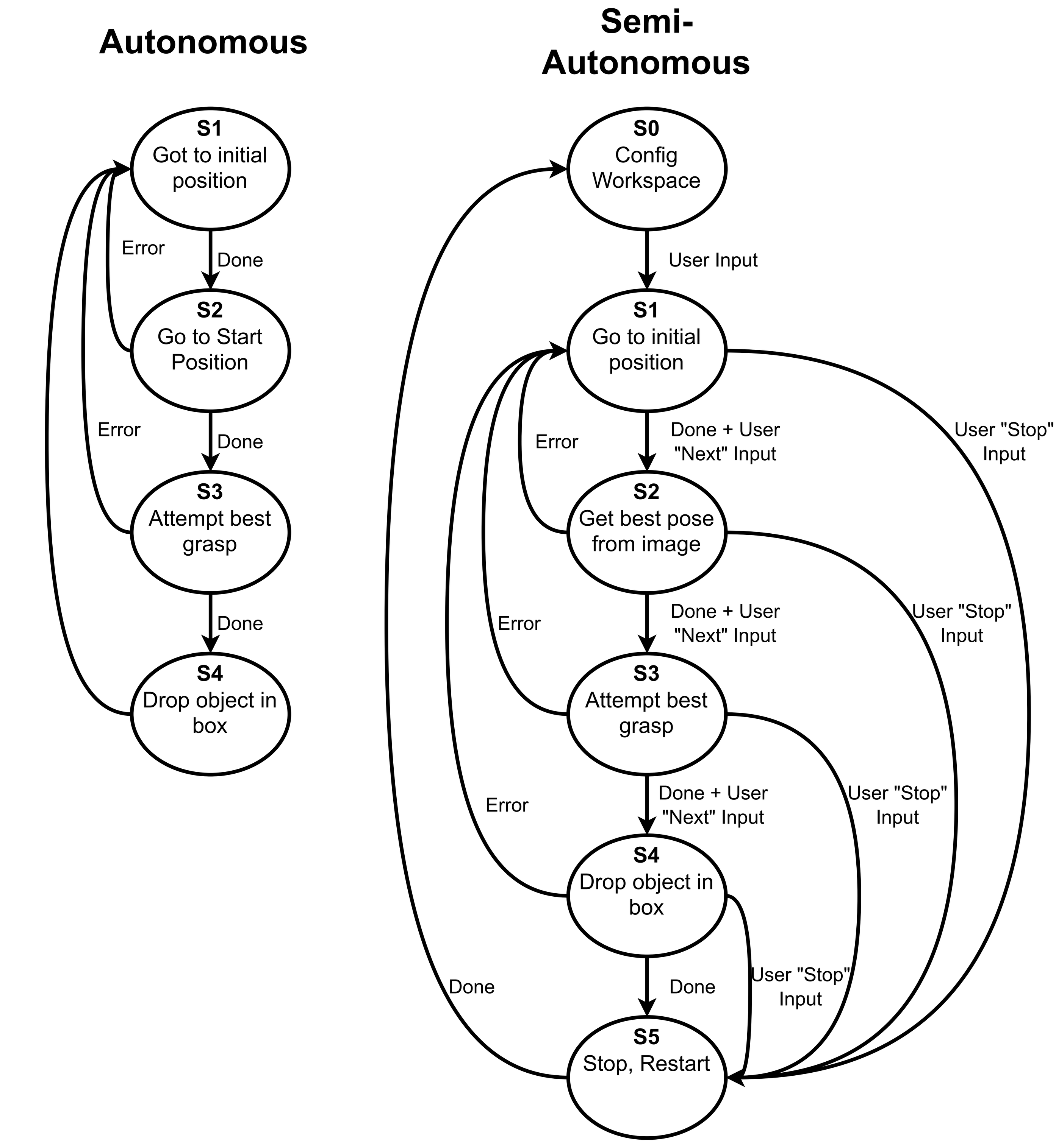

Figure 3: Execution flow for the autonomous (left) and semi-autonomous (right) versions of the grasping system.

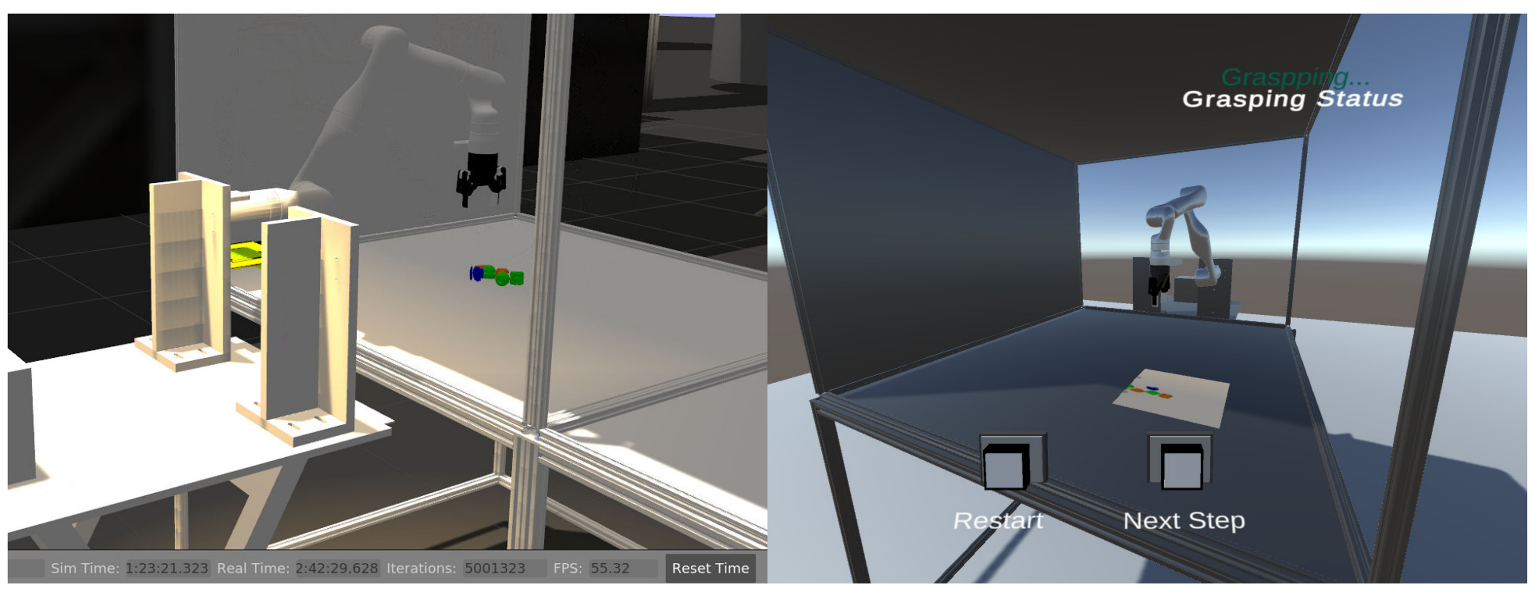

Figure 4: Task execution in the glovebox (left) and the UI view of the digital twin (right), with augmented sensor view, user inputs and state messages.

Reference:

[1] D. Morrison, P. Corke, and J. Leitner, "Closing the Loop for Robotic Grasping: A Real-time, Generative Grasp Synthesis Approach," *arXiv:1804.05172 [cs]*, May 2018, arXiv: 1804.05172. [Online]. Available: http://arxiv.org/abs/1804.05172 (visited on 03/24/2020).

[2] D. Morrison, P. Corke, and J. Leitner, "Egad! an evolved grasping analysis dataset for diversity and reproducibility in robotic manipulation," *IEEE Robotics and Automation Letters*, vol. 5, no. 3, pp. 4368-4375, 2020.

MANCHESTER 1824 The University of Manchester
RACE
UK Atomic Energy Authority
INDUSTRIAL STRATEGY
UK Research and Innovation