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Computer Aided Design of Self-Learning Robotic System Using Imitation Learning

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Abstract. Artificial intelligence (AI), imitation learning, big data, cloud and distributed computing, robotics cells, and information communication technology, are some of the key tools and elements of the future digital and smart manufacturing facility. There are a number of challenges that digital and smart manufacturing is facing, especially with the complication of AI (i.e., machine, deep and cognitive learning) algorithms, great amount of data to process, and essential complex coding required, which makes immediate changes needed in manufacturing facilities not straightforward. This is notable in small manufacturing cells which is an integrated part of future smart factories such manufacturing facilities are usually needed some annual and regular updates to meet the update in the design specifications of next generation of products. Imitation learning is offering a great opportunity to overcome these challenges and simplify such complications, where human skills, ability to perform specific tasks, knowledge, and talent could be transferred. This is conveying the knowledge, and skills transfer using imitation learning. However, smart manufacturing and industrial revolution needs robotics cells that has skills beyond this, especially when it comes to process optimisation. Therefore, deep imitation learning could come in to help in the development of self-learning robotic systems and cells. Of course with the powerful tools such as distributed computing, blockchain, cloud computing, edge computing, and 5G the collaboration between such self-learning robotic cells will be possible. This will certainly not eliminate human existence but will enhance the manufacturing environment. This paper is focused on presenting the outcomes of CAD simulation and modelling phase of the ongoing research programme that focused on developing a self-learning robotic system using imitation learning. CAD tools have been used and some initial results is presented. Further work is still undertaken, and this will focus on learning from more than one expert, optimisation, impact of dynamic manufacturing environment.

Keywords: Imitation learning, Self-learning robotic, CNN, Resnet-50, Relu

1. Introduction

In the very near future robotics systems, Artificial Intelligence (AI), and imitation learning will with no-doubt transformed productivity, particularly in the manufacturing and production industries. As industrial automation will have the potential to reduce human intervention in dangerous or harmful places such as chemical production industries, nuclear energy section and many more. Over the last decade, robotic systems

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have become sophisticated, powerful and, are increasingly moving toward more service-oriented positions. Imitation learning and human-robotic systems interaction are crucial for enhancing robotics cells intelligence and ability to collaborate with humans [1]. Imitation Learning is a technique for learning a behaviour policy by imitating it. Demonstrations are typically presented as state-action trajectories, with each pair indicating the action to be taken in the state being visited [2]. The demonstrated acts are frequently used in two ways to learn the behavior policy. The first, known as Behavior Cloning (BC), uses the action as the target label for each state, and then uses supervised learning to acquire a generalized mapping from states to actions. Another approach, known as Inverse Reinforcement Learning (IRL), looks at the demonstrated behaviors as a series of decisions and seeks to develop a reward/cost function that makes the demonstrated decisions ideal [3]. Recently, there are some ongoing industrial initiatives and research to use robotic cells to execute human tasks in the smart factory [4]. However, there are many challenges that industrial applied research programmes must investigate to present a realistic solution. In this paper, one of the possible realistic solutions based on self-learning robotic system is presented. The current state of the art of the technology, architecture, and CAD simulation, modelling and design is covered and some of the initial results obtained from the simulation and modelling is introduced.

2. State of the Art of Technology

Self-learning robotic cells is a combination of a robot system, intelligence, and sophisticated computing tools [4]. What makes self-learning robotic cells different from traditional ones is that the robot can sense its environment, interpreted data, make decision, and act accordingly [5]. The great advantageous that self-learning robotic system based on Imitation Learning offer are, it will not depend on specific complex programming as it will be trained, learn from experts, and use various optimisation processes to react as per the target and planned scenarios requirements. This will enable them to autonomously adapt to manufacturing environment changes [6]. Self-learning robotic system can be closely related to adaptive control, reinforcement learning and developmental robotics which considers the problem of autonomous lifelong acquisition of repertoires of skills. Example of skills that can be learned includes and not limited to, sensorimotor skills such as locomotion, grasping, active object categorization, as well as interactive skills such as joint manipulation of an object with a human peer, and linguistic skills such as the grounded and situated meaning of human language. Learning can happen either through autonomous self-exploration or through guidance from a human teacher, i.e., robot learning by imitation.

Imitation learning is a technique that teaching robots' new skills. Obtaining demos suited for understanding a policy that translates from raw pixels to actions, on the other hand, can be difficult [6]. It has the possible capability to solve precise manipulation challenges as it does not require an environment model or pre-programmed robot behaviour.

In the real world, a Transformer, a self-attention architecture version, is used to handle dual-arm manipulation tasks via imitation learning. Using an actual robot, the suggested approach was evaluated on dual-arm manipulation tasks [8]. In general, characteristics collected from demonstration data are used in behaviour learning for imitation learning. In addition, employ Human-robot software to gather demonstration data and a deep convolutional network to represent policies. Experiments with 3D realistic robotics simulators indicate that the robot can learn to seek for and dribble the ball [9]. It is predicted that robots will be able to mimic human tool handling abilities using a deep neural network, albeit a large quantity of training data may be necessary. Based on the form of a broom and data stored from prior experience, the suggested system can predict the starting parameters [10]. The needle threading challenge can be solved using imitation learning approach inspired by the gaze-based dual resolution visuomotor control system in humans. First, the gaze motions of a human operator teleoperating a robot were recorded. To get close to the target, using a low-resolution peripheral picture [11]. Approaching Robot Eye Surgery by the Integration of Imitation Learning and Optimal Control, Accurate control of the sensitive retinal tissue is essential for a successful surgical result during retinal microsurgery. During surgery, the doctor's ability to judge depth is hindered by an isometric perspective to learning to anticipate related target location on the retina to automate the tool-navigation task [12]. Inverse kinematic controller with neural networks for real-time delta robot trajectory control. The control approach is entirely data-driven, and no prior knowledge of the robot's kinematics is required. To test the suggested controller, several simulations and tests are carried out [13]. Without calibration, the absolute positioning inaccuracy of robots can approach several millimeters. This researcher looked at the robot calibration challenge through the viewpoint of machine learning. It provides the first open-access dataset in this field, "Robot Cali" allowing machine learning experts to enter the field of robot calibration [14]. Interactive Machine Learning (IML) is a technology that uses neuro-evolutionary machine-learning approaches to incorporate human input into the creation of algorithms. Even though participants trusted IML-produced search plans significantly less than plans developed using a non-interactive ML technique, preliminary findings show that IML-generated search plans were preferred. The findings establish the groundwork for further research on how to properly combine human and machine learning behaviour [15]. Therefore, it is very much expected that Self-learning robot cells using imitation learning is the novel solution that will, reduce human intervention, especially in most harmful places industrial applications, improve productions and manufacturing environment and future smart factories configuration, and reconfiguration facilities.

3. Self-Learning Robotic System Architecture

Figure 1 illustrates the self-learning robotic system architecture. It has four major units, and these are, an interactive interface unit for human demonstrator and expert, behavior segmentation, imitation learning, and robotic system. The working principles are the system determine the condition of the joint angle, the gripper, and the RGB-D sensor. A forward kinematics analysis is required to find the position of the joint angle and gripper. And to identify and detect the colors of objects, an advanced webcam that acts as an RGB-D sensor is used. The human demonstrations and movements will be transferred and recorded, automatically segmented into movement building blocks, and labelled according to known movement classes. The segmented trajectories are mapped to the robot workspace and imitated. As per the modular design and adopted approach, the learning process can be automated for different environments. This can be made possible by a minimal amount of configuration and reconfiguration to integrate the available preceding knowledge about the robotic system target system and or intended scenario. It is also possible that demonstrations of the same task can be transferred to different systems by configuring general robot-related properties, like kinematic structure of the robot, type of gripper and default joint configuration, and definition of a rotation matrix to map the robot's end-effector rotation to the human hand orientation.

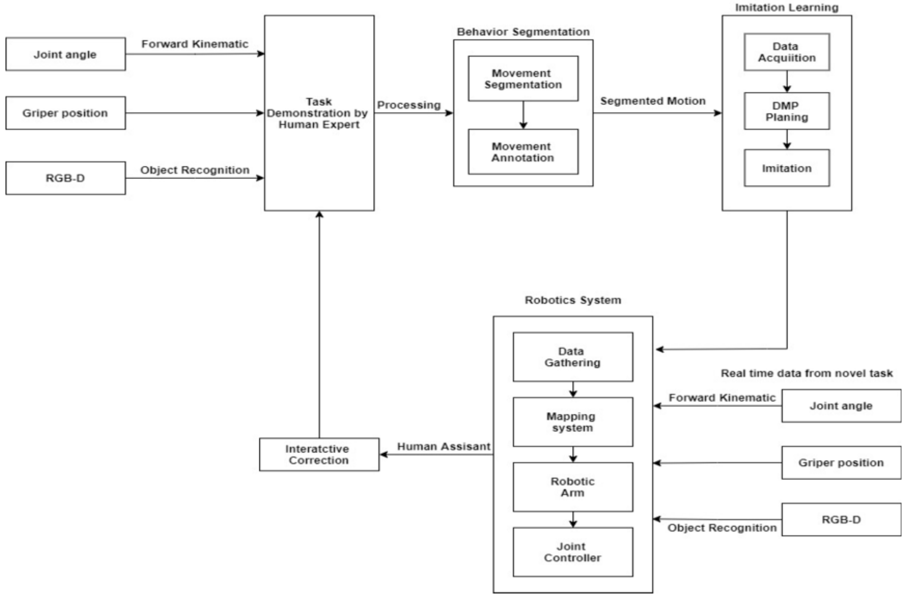

Figure 1. Self-learning robotic system architecture and four major units of the system

4. CAD Design, Simulation and Modelling of Self-Learning Robotic System

Self-learning robotic systems can adapt to complex and dynamic environments, which is one a fundamental challenge in smart manufacturing. To resolve this issue, Convolutional Neural Networks (CNNs) are used in conjunction with the latest path planning methods [16]. This approach uses CNNs to map raw image data directly to waypoints and speed values. Based on those values, it creates a minimum trajectory. The robot controller receives trajectory signals and follows them. It is necessary for robot cells to navigate to waypoints to reach their destination. Curvature can interrupt a waypoint-specified trajectory. This type of interruption should be adjusted by the waypoint tracking controller. The purpose of the step of the research programme is to develop a trajectory tracking control approach for self-learning robotic system. The controller's design considers the trajectory of objects that pivot quickly. According to Figures 2 and 3, CAD model, a robot can track waypoints and follow trajectory and grasp the ball following defined paths and place it in its indicated location.

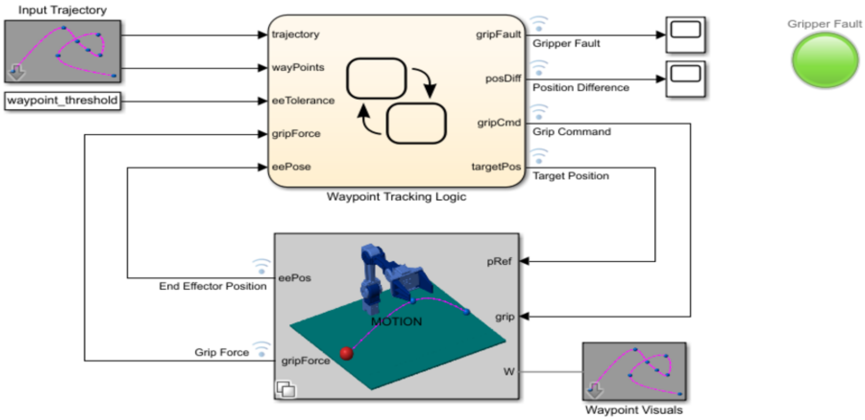

Figure 2. CAD model of self-learning robotic system

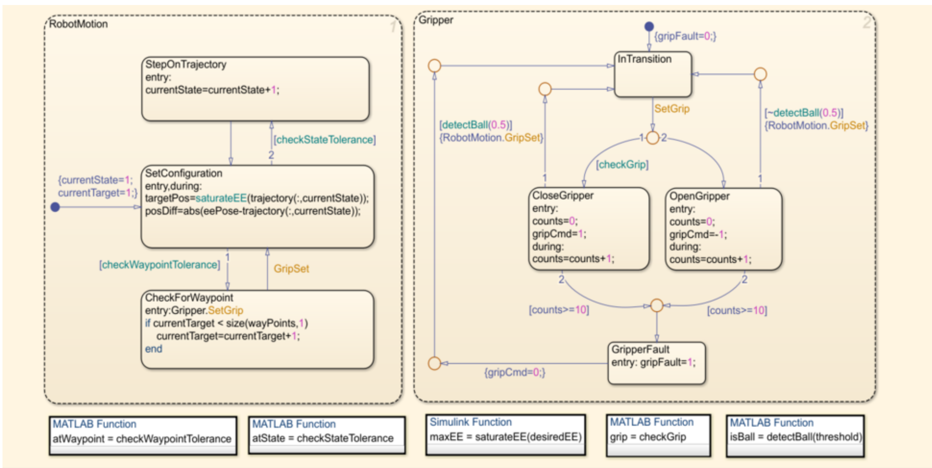

Figure 3. CAD model of self -learning robotic control system for Trajectories Pathways

5. CAD Initial Findings, and Results

The initial results of CAD model are obtained using Resnet-50 as shown in figure 4. CNN’s classification method has been used to classify, and separate data in image formats. The model is used to detect the trajectory points of objects and train based on classification, and separation as illustrated training data in figure 5.

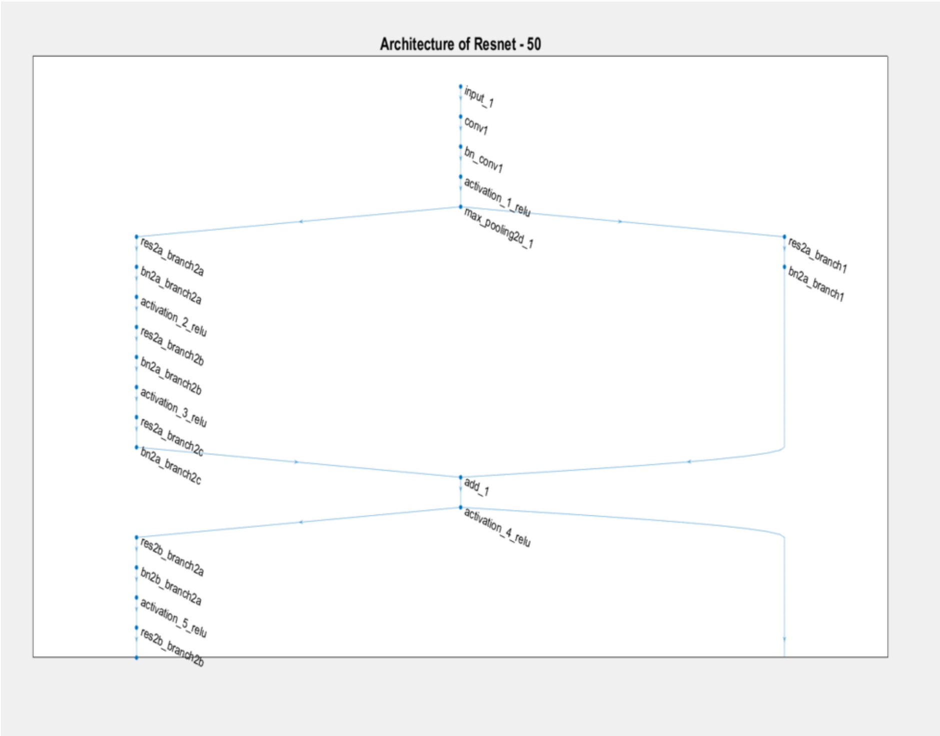

Figure 4. Resnet-50 Model with CNN's

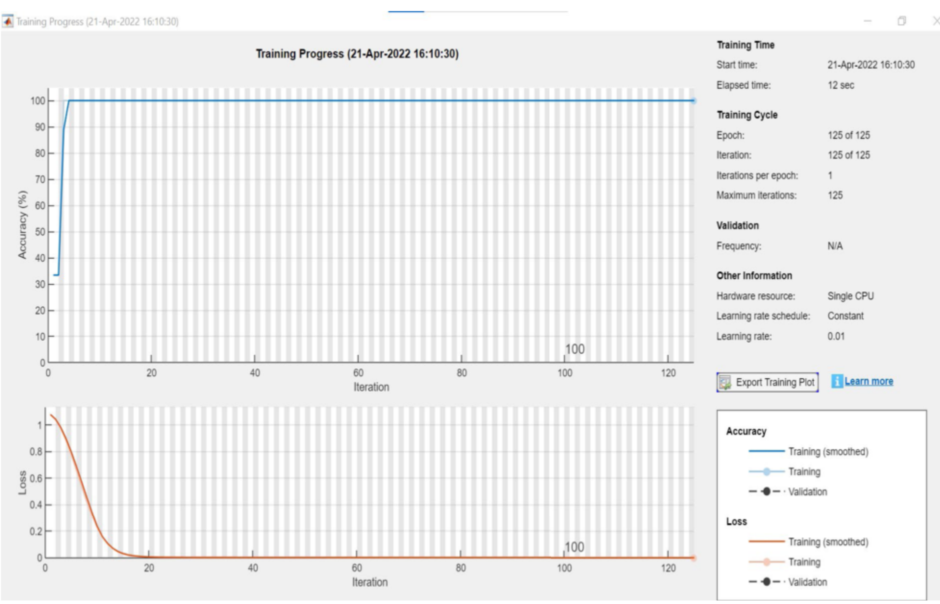

Figure 5. Initial Analysis for training accuracy

6. Conclusion and Future Work

This paper presented the CAD model of self-learning robotic system using imitation learning. CAD tools have been used to develop the model. The model enables flexible waypoint point trajectory tracking in robotic system movement and ball sensing prediction based on grippers positioning. The use of CNN's classifiers provided initial results in behavior learning, object recognition, data classification, data segmentation, segregation and image processing. The model is still under refinement and more work needed to obtain a more accurate results, this is to consider the manufacturing environment noise, and any possible unnecessary data detected during the mapping process. The Further work will also focus on, learning from multiple experts, optimisation, impact of trajectory and process.

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