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An Industrial Self-Learning Robotic Platform Solution for Smart Factories Industrial Applications Using Machine and Deep Imitation Learning

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Abstract. Smart Factory is a key platform for recent industrial revolution 4.0 and industrial robotic platform solutions using Artificial Intelligence are an integral measure of its cell's configuration and reconfiguration. There are two different methods of machine learning used in industrial collaborative robotics systems, Computer Vision Machine Learning and Imitation Learning. Computer vision is a classical use of machine and deep learning methods and it needs a complex, expensive resources and is not suitable for various types of manufacturing automation environment. Imitation Learning is the most fascinating method, and the recent evolving industry is interested on it. The main aim of this research programme is to develop a self-learning robotic system platform solution using Machine and Deep Imitation Learning for smart factories' industrial applications. A self-learning robotic system using deep imitation learning can reduce working time and give a less human error when performing high-precision processes. It can also improve the ability to configure robotic platform to facilitate a more flexible decisions and cost-effective manufacturing.

Keywords: Industrial Robot, Automation, Degree of Freedom, Smart Factories, Imitation Learning.

Imitation Learning

1. Introduction

Artificial Intelligence, self-learning collaboration robotic systems, and industrial automation are developing very rapidly. AI and industrial automation are research areas to enhance and strengthen human potentials, increase productivity, and are nowadays moving from simple reasoning towards human-like cognitive abilities. This consents the urgent need to implement smart factories to enrich manufacturing process facilities to tackle the enormous challenges facing UK to develop a more flexible digital manufacturing environment using green technology. Smart Factory is a key platform for industrial revolution 4.0 and industrial robotic systems platform solutions using Artificial Intelligence are an integral measure of its cell's configuration and reconfiguration ability. There are two different methods of machine learning used in industrial collaborative self-learning robotics systems, Computer Vision Machine Learning and Imitation Learning

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(Osa, et al., 2018). Computer vision is a classical use of machine and deep learning method and it needs complex, expensive resources and is not suitable for various types of manufacturing automation environment (Park, Li, & Hong, 2020). Imitation Learning is the most fascinating method and the recent evolving industry is interested on it. In the Imitation Learning scenario, a robot can programme by demonstrating how to complete a task. For example, someone could show a collaborative robot how to grasp an object by guiding the robotic arm the first few times (Association, n.d.); (Bagnell, 2015). In this way, the robot would learn to grasp the object on its own. Such a method offers a flexible manufacturing process environment that can reduce working time, a complication in the development lifecycle and providing less human error when performing high precision processes systems (Osa, Multimodal Trajectory Optimization, 2020). It is also one of the most suitable approaches to meet flexible, programmable and fixed industrial automation requirements. Since its flexible software platform can usually be modified easily by expert training to meet the end-users particular manufacturing process provisions and demands. This makes it an economical, portable and low-maintenance platform solution for many industrial applications, where there is a need to manufacture a variety of products and parts, specific classes of product changes and fixed sequences of processing or assembly and or high-risk processing environment.

The self-learning robot using machine and deep imitation learning is an autonomous system capable of learning from experts, sensing the surroundings-manufacturing environment, carrying out the necessary calculations, make relevant precise decisions and carrying out actions in a real manufacturing environment (Jadeja & Pandya, 2019); (Katz, 2017); (Shyam, Hao, Montanaro, & Neumann, 2020). The main goal of imitation learning algorithm is to learn a policy that reproduces the behavior of experts who demonstrate how to perform the desired task. To perform imitation learning, there is a need to develop a system that records demonstrations by experts and learns a policy to reproduce the demonstrated behavior from the recorded data. There are multiple ways of recording the behavior of experts such as motion capture systems and teleoperated robotic systems record data from expert behavior (Osa, et al., 2018); (Osa, Multimodal Trajectory Optimization, 2020); (Judah, Fern, Tadepalli, & Goetschalckx, 2014).

The development of an imitation self-learning system must go through several choices to formalize the platform solution for specific industrial applications. These choices are can be summarized as follow: access to the reward function: imitation learning or reinforcement learning, parsimonious description of the desired behavior: behavioral cloning / duplicating or inverse reinforcement learning, access to system dynamics: model-based or model-free, similarity measure between policies, features and policy representation (Osa, et al., 2018); (Association, n.d.); (Bagnell, 2015); (Osa, Multimodal Trajectory Optimization, 2020). The imitation self-learning systems are normally developed to control different processes using near real-time advanced embedded systems and programmable logic controller technology, multi degrees of freedom actuation systems, a combination of the high standard array of sensations technology and high tech-self-learning algorithms (Cavalcanti & Santana, 2017). Recently, the self-learning robotic arm using the imitation learning method has been used for trajectory planning of manipulators placed on small spacecraft. This was design for regional transparency in future space missions and limited human interruption from the ground station, a 7-Degrees of Freedom (DoF) robotic arm was developed and projected to perform several tasks such as debris retrieval, on-orbit operation and installation (Shyam, Hao, Montanaro, & Neumann, 2020). The research focused on the problem of decreasing attitude interference to spacecraft buses as the arm reaches out to discover debris. The learning method is offline and computationally very effective for discovering new routes after deployment. The future scope of a researcher is to test the trajectory-planning algorithm in a Future Space Debris Removal Orbital Manipulator (SDROM), which has a similar microsatellite spacecraft bus as Remove DEBRIS (Shyam, Hao, Montanaro, & Neumann, 2020); (S.Aglietti, et al., 2017). The robotic device provides complex, adaptive and autonomous interaction with real-time performance assessments and feedback to acquire imitation competencies. In a consumer analysis for children with ASD (Autism Spectrum Disorders) who usually create control samples, the device has been checked. In the consumer analysis, the system's output was often compared to that of a human therapist. The findings suggest that the robotic device built has a strong tolerance to the target population, has involved children with ASD more than a human therapy, and has provided a comparatively better outcome than a human therapist (Zheng, et al., 2014). This research offers a new paradigm for imitation learning at the cognitive level. It uses parsimonious cause-and-effect logic to understand and recognized the demonstrated abilities and describe or assert their own actions. Throughout the next generation of autonomous systems, the study is used to help analyse the neuro-computational cognitive control, contributing gradually to systems that are more versatile and transparent (Katz, 2017). This initial investigation into the current technology of this programme scope state of the art reveals that there are still several challenges in self-learning systems platform solution in both hardware and software.

2. Self-learning Robotic System using Machine and Deep Imitation Learning

2.1 System Architecture

The System architecture is shown in Fig. 1, Robot imitation learning has recently become one of the favorite research areas globally. The method of imitation learning robotic manipulation is mainly divided into three sections: demonstration, representation, and the imitation learning algorithm.

i. Demonstration

The core of the imitation learning process is the development of operational intelligence (Attia & Dayan, 2018), which is the technique of obtaining knowledge from an expert through "observation". Now, there are two forms of imitation learning presentation techniques: indirect demonstration and direct demonstration (Kumar, Gupta, Todorov, & Levine, 2016). Indirect presentations do not require physical contact with the robot and are instead set up in a separate environment. Indirect learning of wearable sensors captures measurements, in resulting more accurate and informative (Wana, Lu, Wu, & Harada, 2016); (Sermanet, et al., 2018); (Fang , Sun , & Liu, 2017). Direct demonstration obtains instructional examples directly from the robot and can be divided into two types: 1) Kinesthetics training, which entails the operator making eye contact with the robot and guiding it through a specific operation. 2) Teleoperations in some cases are simply teaching based on pose or trajectory, with little information about the actual procedure (Esfahani & Ragaglia, 2018); (Zhang, et al., 2018); (Gašpar , Nemec , Morimoto , & Ude, 2018).

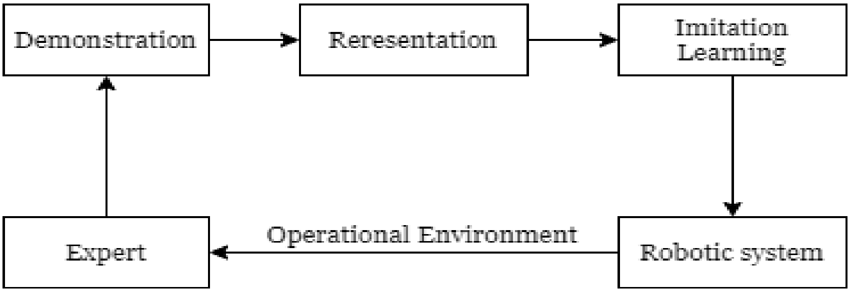

Figure 1: Imitation learning in Robotic Manipulation.

ii. Representation

The sample can include a variety of features after the demonstrator completes the manipulation. It is critical to classify the demonstration adequately and effectively. 1) Symbolic representation is a mental representation of robots on a high level in imitative learning. The same operating principle allows different tasks to be completed. It provides a practical solution to tackling difficult problems of multi-step learning. 2) The trajectory characterized is defined as a primitive motion (Yang, Wang, Cheng, & Ma, 2017). It describes the human body by probability and extends it to the robot. During trajectory characterization, as many dynamic features as possible are needed in the sample. 3) The action-state space is described differently from the characteristics of symbolization and trajectory. By corresponding control behavior, the mapping relationships between the task-related requirements and the system status are established. In recent years, several methods of machine learning have been successfully used for the identification of tactile material, including nearest neighbour, vector assistance, the Gaussian process and nonparametric Bayesian training. The analysis of the classification of multimodal organizational information is essential for imitational learning and it can help to learn in the study of long-term information characterization.

iii. Machine and Deep Imitation Learning

Imitation learning is a technique that enables skills to be transferred from humans to robotic systems. The goal of imitation learning is to learn a policy that reproduces the behavior of experts who demonstrate how to perform the desired task. To perform imitation learning, we need to develop a system that records demonstrations by experts and learns a policy to reproduce the demonstrated behavior from the recorded data. There are multiple ways of recording the behavior of experts. For example, motion capture systems and teleoperated robotic systems record data from expert behavior. Deep learning models represent a new learning paradigm. Deep learning is a subtype of machine learning in artificial intelligence that involves models which can learn autonomously from unorganized or unlabeled information. Deep neural learning and deep neural network are other terms for the same thing. Also known as deep neural learning or deep neural network (Chassagnon, Vakalopolou, Paragios, & Reve, 2020). Latest innovations in image processing and voice recognition have sparked widespread interest in this area, since it appears that applications in a variety of other disciplines using large data are also feasible (Emmert-Streib, Yang, Feng, Tripathi, & Dehmer, 2020).

3. Research Programme Scope and Future Work

To achieve the aim and objectives, three main research methods will be used during the development life cycle of this research and these are exploratory, constructive and empirical methods. Empirical methods will consider records demonstrations (i.e. using either motion capture systems and teleoperated robotic systems) by experts and learns a policy to reproduce the demonstrated behavior from the recorded data. The three methods will allow identifying the self-learning robotic system platform solution key machine and deep imitation learning resources, design specifications, system architecture, defining the system main hardware design choices & algorithms & software, and then test the feasibility of the design using empirical evidence. A prototype will be developed and will be tested based on design specifications and industrial case studies need to verify the potential of the platform solution from applied research, economic and environmental impact point of view. Also, discuss critical evaluation in future for deep learning.

4. Conclusion

In the Imitation Learning scenario, a robot can programme by demonstrating how to complete a task. It is also one of the cleverest approaches to meet flexible, programmable and fixed industrial automation requirements. This research paper is to survey a self-learning robotic system platform which is one of the emerging cutting-edge approaches to meet flexible, programmable and fixed industrial automation requirements to meet the various manufacturing needs. The self-learning robot using machine, deep and cognitive imitation learning is an autonomous system that capable of learning from experts, sensing the surroundings-manufacturing environment, carrying out the necessary calculations, make relevant precise decisions and carrying out actions in a real manufacturing environment. Imitation Learning is the most fascinating method and there is a growing interest in it. The development of an imitation self-learning system must go through several choices to formalize the platform solution for specific industrial applications.

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