A Review of Imitation Learning in Natural Human-Robot Interaction

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Abstract. This paper reviews over twenty recent studies on applying imitation learning (IL) to natural human-robot interaction (HRI). Traditional rule-based behavior modeling offers transparency and controllability, but there is a lack of flexibility and adaptability. This motivates the adoption of IL, allowing robots to acquire desired behaviors directly from demonstrations. This review summarizes representative IL applications in gesture imitation, gaze imitation, and contact-rich tasks, highlighting their contributions to enhancing the social interactivity of robots. Current challenges include model collapse, limited interpretability, and difficulty collecting contact-dynamics data. Finally, future research directions are outlined, such as mitigating model collapse through real-data augmented reflow (RA Reflow) and its updated versions, increasing interpretability with the R2RISE framework, and achieving data-efficient IL via multi-sensor fusion and high-dimensional tactile representations from limited demonstrations.

Keywords: Imitation learning, human-robot interaction, gesture imitation, gaze imitation, contact-rich tasks.

1. Introduction

In recent years, Human-Robot Interaction (HRI) technology has become increasingly significant in various machines used daily [1]. In healthcare, socially assistive robots (SARs) are employed in more medical institutions, where SARs are characterized as systems that support users by socially interactive methods [2]. In domestic environments, robots are intended to complete tasks requiring sophisticated interactions with humans, which need mutual understanding [3]. In education, socially interactive robots powered by AI provide a novel way of improving student engagement and learning outcomes [4]. Rule-based design is a conventional approach to modeling robot behavior, which relies on predefined rules. This style offers certain advantages that make it attractive in a particular situation. Transparency is one of the notable benefits as humans program their decision-making patterns. Thus, these robots tend to be more reliable, with decision logic that is easier to understand and verify. Another advantage is controllability. Outcomes from role-based logic are predictable and consistent. That way, developers and users can adjust the response more efficiently. However, traditional rule-based design often lacks flexibility and adaptability. If the answer to the input is not given in advance, the reaction is usually disappointing. Moreover, rule-based models typically exhibit a fixed nature and characteristics. If users prefer a different personality, these robots find it difficult to satisfy the requirements [5]. Imitation learning can be employed as an effective training method to mitigate these issues. Robots can learn desired behaviors through imitation learning by simply demonstrating them, without explicit programming [6]. Although there are many examples of combining imitation learning and HRI, there is still a lack of conclusions about the most recent cases. Because of this, this paper reviews recent applications of imitation learning in HRI to provide a general idea of how this technique contributes to more flexible and socially interactive HRI.

2. Background on Natural Human-Robot Interaction

2.1 Human-robot Interaction

Human-robot interaction (HRI) is a research area classified as a field of robotics and has developed rapidly in recent years. It promotes robotics development and provides an excellent opportunity to play an active role in daily human activities. When discussing HRI, it refers to the concept of understanding, design, development, and evaluation of robotic systems that can be directly used by or cooperate with humans. Research about HRI involves a wide range of areas, including industry, public services, education, healthcare, and rehabilitation [7]. The interaction between robots and people requires natural communication, which consists of verbal and nonverbal behaviors. Although verbal language is often dominant in human communication, nonverbal behaviors, including eye gaze and gestures, are significant in expressing emotion and reinforcing verbal content. To be more specific, eye gaze can assist in capturing user attention, making conversation more engaging, and enhancing the fluency of human-agent interaction [8]. In addition to gaze, gestures enable users to express their meaning more efficiently and conveniently than verbal language in specific contexts [9]. For instance, when someone wants a tool in a collaborative task, pointing can indicate the location of the desired item more efficiently. Another example of nonverbal communication is head movement. This nonverbal interaction can improve the social expressiveness of robots and contribute to a more natural and human-like interaction experience [10].

2.2 Imitation Learning

To address the challenges above, a shift from conventional rule-based modeling to AI-driven behavior modeling has been advocated [11]. Imitation learning is one of the possible solutions. Imitation Learning (IL) enables agents to generate answers by replicating observed behaviors through a relatively straightforward framework. The general idea of its principle is learning from the demonstrations and using the knowledge to resemble these original behaviors in comparable backgrounds. One application of imitation learning in the continuous control domain is autonomous driving. IL can enable autonomous vehicles to mimic expert driving strategies in complicated and changing scenarios. Imitation learning relies on demonstration data. Two primary sources can generate the materials used to train IL models: human experts or artificial agents. Usually, training data originates from human experts. However, Chen *et al.* discovered some advantages of employing artificial agents to train IL models with their teacher-student framework. In this system, a student agent without any information was taught by another agent with access to privileged knowledge. This student agent studied efficiently because it can consult the teacher and receive demonstrations under similar environmental settings, while traditional IL suffers from the kinematic shifting problem [12].

3. Applications of Imitation Learning in HRI

3.1 Gesture Imitation

A study by Calinon and Billard [13] provides the basis for gesture imitation in humanoid robots. In this work, the performance of two incremental training strategies—direct update and generative methods—is compared with that of a standard batch training method. Two different teaching modalities are employed to diversify the teaching approaches: teaching with motion sensors and kinesthetic teaching. In the former, motion sensors capture users' upper-body movements, including arms and head. At the same time, users should demonstrate gestures to the robots. In the latter, users physically teach the robot by adjusting its limbs to the targeted positions. In that way, robots can replicate the gesture through repeated correction. The experiment results with a HOAP-3 humanoid robot indicate that mixing both modalities efficiently delivers new gestures. Besides, the results support that these two incremental teaching approaches effectively catch and copy human movements.

Imai et al. [14] recently presented an autonomous robotic arm that learns teleoperated gestures through instance segmentation and haptic feedback. This study aims to integrate teleoperation with autonomous robot control, realizing the collaboration between humans and robots in completing tasks. Imitation learning is an appropriate way to automate robots. To mitigate the downsides of action chunking with transformers (ACT) policy model, the YOLOv8-seg instance segmentation model is applied to outline the boundaries of the arm and the target object. Moreover, the regions corresponding to the robot arm and the object of interest are identified using the segment anything model (SAM). In the experiment, the robot was required to grasp an orange from a table and place it into a container. The result shows that the suggested model has a 66% probability of accomplishing the assigned task with segmented image input.

3.2 Gaze Imitation

Recent research by Chen *et al.* [15] attempted to use the gaze behavior to improve the prediction of steering in vision-based autonomous driving. In this paper, the author mentions that prior studies suggest expert gaze patterns provide valuable guidance for beginners during their learning process. To fulfil the target, they introduce a gaze-modulated dropout mechanism that embeds gaze cues directly into the learning process instead of providing them as external inputs. According to the experimental outcomes, the method successfully increases the network's capability to adapt to unknown environments. Specifically, this gaze-modulated dropout results in a 23.5% reduction in steering command prediction error compared to uniform dropout techniques. Furthermore, this approach increased the average driving distance without violations by 58.5% when simulating a closed loop. As a result, the model using gaze modulation has a lower predictive uncertainty, which means it becomes more reliable.

3.3 Contact-rich Tasks

Previous research proves teleoperated demonstration data can be valuable for learning tactile-based policies. In most cases, the visual input is the first option for the demonstration when directing the robot’s actions. This leads to a problem of difference between the sensing modality, visual data, and the desired modality, tactile information. Yu et al. propose a new approach named MimicTouch to address this trouble in their research [16]. This method enables policy learning directly from human hand demonstrations. Another innovative point is the human tactile demonstration collection system. With this system, the portion of usable demonstrations in data collection reached 83.3% which is higher than the other two test methods: space mouse teleoperation (38.5%) and hand teleoperation (58.5%). The experimental part chose insertion tasks, the core difficulties faced in contact-rich manipulation. Based on the results, MimicTouch achieved a higher success rate than the open-loop policy in each assigned task. It highlights the strong generalization ability of the MimicTouch policy across various challenging domains.

4. Challenges and Limitations

As training an AI model needs a large amount of data, some researchers may use AI-generated data as a substitute for expert demonstration. It has been observed that inputting information produced by other models as training data can lead to a “model collapse” concern. In detail, models that encounter “model collapse” would lose the actual data distribution, which can be described as a degenerative phenomenon. After changing the data distribution, the outcomes of these models are polluted. If future models are trained with these polluted results, their perception will be distorted. The distribution shifted due to the accumulation of three error categories: statistical approximation error, functional expressivity error, and functional approximation error [17].

Another difficulty imitation learning faces is the lack of interpretability. Some imitation learning models involve deep neural networks (DNNs). One of the characteristics of DNNs is that the knowledge gained from the demonstration is complicated and not understandable for humans. Because of this, imitation learning cannot be employed in safety-critical systems [18].

Some specific challenges must be solved when applying imitation learning to contact-rich tasks. Firstly, recording contact-rich dynamics using standard methods is hard due to their nonlinear feature. Another problem is the lack of options for data collection. The development of wearable tactile technologies remains difficult, and their influence on research and industry applications is negligible. Ultimately, the richness of the data significantly reduces both data efficiency and the ability to generalize to unfamiliar scenarios or items [19].

5. Future Directions

To address model collapse (MC), future work can further explore the Real-data Augmented Reflow (RA Reflow). Usually, model collapse can be prevented with the help of real data. Through research, Rectified Flow and its Reflow algorithm can also be employed to solve the problem of model collapse. However, these two methods cannot be combined easily. Because of this, RA Reflow is presented as a solution, along with two improved versions called Online Real-Data Augmented Reflow (ORA Reflow) and Real-data Argument Stochastic Reflow (RAS Reflow), respectively [20].

Recent research proposed a novel Remove and Retrain approach via Randomized Input Sampling for Explanation (R2RISE) to improve interpretability. This method hides random frames from the demonstrations and assesses how agents trained after modifying the inputs. The general idea is to treat the entire demonstration as one complete image, and the pixels in this image are the frames input. R2RISE can provide explanations independent of model type. Future studies can investigate how to produce more rigorous explanations and their real-world applications [21].

Advances in wearable tactile sensing technology are expected to provide better-quality demonstrations in contact-rich tasks. Furthermore, the next step could be researching how to improve generalization and reduce the reliance on large datasets. For example, the multi-sensor fusion framework realizes data-efficient imitation learning by utilizing high-dimensional tactile representations extracted from a limited number of demonstrations [22].

6. Conclusion

Based on insights from over twenty recent studies, this review addresses how imitation learning (IL) can be employed in natural human-robot interaction (HRI). By contrasting IL with traditional rule-based behavior models, it was shown that IL can provide greater adaptability and the capacity to extract behavior rules from demonstrations. In this case, robots can engage more naturally with humans. This discussion highlighted successful applications in gesture imitation, gaze imitation, and contact-rich tasks. Data efficiency, interpretability, and robustness limitations are also included. To solve these challenges, some recommendations for future research were proposed. This review does not specify the literature selection criteria, such as the time range of databases and exclusion conditions. Future work should include a clearly defined literature search strategy and selection process, potentially illustrated with a PRISMA flow diagram. This would clarify why specific articles were chosen and ensure that the review covers the mainstream research in the field. This study's main contribution lies in providing a structured synthesis of recent IL research within HRI, clarifying current challenges, and illustrating possible future directions that may guide the development of more natural, adaptive, and socially intelligent robotic systems.

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