

# A survey of robot learning from demonstrations for Human-Robot Collaboration

Jangwon Lee  
School of Informatics and Computing  
Indiana University  
Bloomington, Indiana, USA  
Email: leejang@indiana.edu

**Abstract**—Robot learning from demonstration (LfD) is a research paradigm that can play an important role in addressing the issue of scaling up robot learning. Since this type of approach enables non-robotics experts can teach robots new knowledge without any professional background of mechanical engineering or computer programming skills, robots can appear in the real world even if it does not have any prior knowledge for any tasks like a new born baby. There is a growing body of literature that employ LfD approach for training robots. In this paper, I present a survey of recent research in this area while focusing on studies for human-robot collaborative tasks. Since there are different aspects between stand-alone tasks and collaborative tasks, researchers should consider these differences to design collaborative robots for more effective and natural human-robot collaboration (HRC). In this regard, many researchers have shown an increased interest in to make better communication framework between robots and humans because communication is a key issue to apply LfD paradigm for human-robot collaboration. I thus review some recent works that focus on designing better communication channels/methods at the first, then deal with another interesting research method, Interactive/Active learning, after that I finally present other recent approaches tackle a more challenging problem, learning of complex tasks, in the last of the paper.

## I. INTRODUCTION

Robot learning from demonstration (LfD) is a promising approach that can transfer many robot prototypes remaining in research laboratories to the real world since it typically does not require any expert knowledge of robotics technology for teaching robots new tasks. It thus allows end-users to teach robots what robots should do based on their own requirements at their place. Existing research recognizes this attractive feature of LfD, so there is a growing body of literature that employs the theme of LfD for their research [1]–[3].

LfD also has been attracting a lot of interest from researchers in the field of Human-Robot Interaction (HRI) because it helps robots to learn new tasks that are infeasible to be learned using pre-programming like personal requirements as their human counterparts. Furthermore, the HRI perspective can help to build a robot learning process more efficiently (e.g., a human user can correct the robot's behaviors during interaction and highlight important points of the new tasks).

In order to employ the concept of LfD for human-robot collaborative tasks, however, researchers should not only consider robot learning algorithms or techniques, but also take into account many human-centric issues such as the

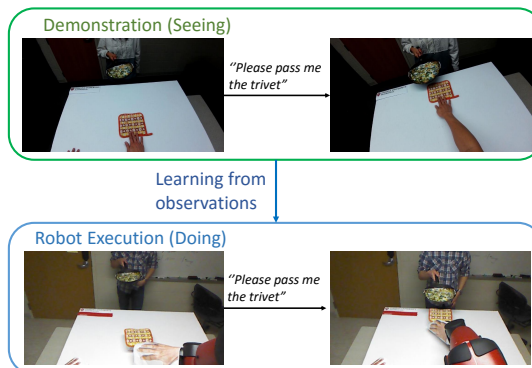


Fig. 1. Robot learning from demonstration (LfD) enables robots automatically learn a new task from observations. End-users can teach robots a new task what robots should do without any expert knowledge of robotics technology.

human partner's feelings and intentions during collaboration phases. Moreover, here are a number of important differences between the approaches that are used by HRI researchers and other robotics researchers who have different perspectives even though both fields work under the same LfD paradigm. One major difference is that HRI researchers tend to be more focused on communications between humans and robots, and thus try to extract intentions behind actions and make communications clear while other robotics engineers are more concerned about specific techniques like how to replicate arm trajectories from human demonstrations for accomplishing a certain type of task.

LfD is a broad topic ranging from various machine learning techniques like supervised learning, reinforcement learning, and feature selection, to human factors as well. Researchers with different backgrounds thus employ the concept from different points of view [1]–[3]. There are common theoretical issues in the field such as the *Correspondence Problem* that arise due to a mismatch between the teacher's body configuration and the student's configuration [4] and interface issue to design user friendly interfaces for demonstration (i.e., motion-capture systems [5]) in order to enable non-robotics experts to teach robots new knowledge without any difficulty. However, I more focus on the specifics of this area which apply this concept for human-robot collaborative tasks that have some

different issues coming from human factors rather than to address those common issues in the field.

I begin my review by presenting an overview of LfD approaches for human-robot collaborative tasks. I will then go on to review research that address communication problems between robots and humans in Section 2-A. The approaches that employ *Interactive/Active Learning* methods, what make a teaching/learning process more interactive, will be addressed in the following section (Section 2-B). In the next section, I will introduce some recent work that attempts to teach robots a complex task rather than a single task (Section 2-C). To conclude, I summarize this article in Section 3 with discussion.

## II. LfD FOR HUMAN-ROBOT COLLABORATIVE TASKS

In order to build robots that would work together side by side with humans while sharing workplaces, many human factors should be addressed properly. For example, researchers should handle a safety issue to prevent potential hazards by robots [6] and they also need to consider a human partner's mental states (i.e., feelings, desires, intents, etc.) to make them feel more comfortable with robot co-workers [7], [8]. Moreover, since people perceive and react to robots differently according to their relationship with robots and the appearances of them [9], it is important to consider these factors if we want people treat robots as their "work partner" or "friend." The LfD paradigm cannot be used to teach robots human-robot collaborative tasks without considering the above human factors, despite many attractive points of LfD.

There has been a considerable number of previous efforts to use a LfD paradigm for human-robot collaborative tasks while considering those human-centric issues using different techniques [10]–[13]. Even though each work handles the human factors in different ways, very roughly, we can consider the problems tackled by all of these approaches as a kind of uncertainty minimization problem since most of the problems stem from unpredictable behaviors of humans/robots. Therefore, reducing the uncertainty in communications can be the key concept of these research areas in the success of the learning process.

For example, many HRI researchers focus more on designing a way to help a human user easily understand their robot partner, rather than to develop techniques to just transfer knowledge from a human to a robot for replicating certain motions [7], since it helps increase human's predictability. We as humans tend to feel uncomfortable when we are in unpredictable situations or when we are not able to understand someone's intention or meaning, but we would be comfortable as we become more familiar with the situations or each other by understanding them. As our partner, robots are also required to understand a human partner's mental states for working together, hence many researchers attempt to automatically detect social cues of people using various techniques [14], [15]. We can see details about these research methods in Section 2-A.

Another important perspective to employ the LfD paradigm for human-robot collaborative tasks is to make the learning

process a bidirectional activity rather than passive learning where robots learn new tasks from passively observing human demonstrations [12]. This line of research is called *Interactive/Active Learning* and considers a robot as an active partner that provides feedback to the human teacher during the collaboration phase, and then the feedback can be used for reducing uncertainty in terms of accomplishing to learn new tasks so that that learning process is able to become more efficient [16]. I will give detailed reviews about the active learning methods in Section 2-B.

Learning of complex tasks is another challenge that researchers have recently treated in the field [17]. This is one of the ultimate goals of all LfD based approaches since we want to robots to automatically learn some high-level skills like "pick-up" without teaching them all the arm trajectories to accomplish the task. Although learning of high-level actions is the ultimate goal of the field, there have been few studies that have investigated it for human-robot collaborative tasks [18]. I will present these recent studies in Section 2-C.

### A. Communication

Communication is the most important key for creating a collaborative robot that can work around us (humans). Communication is a bidirectional activity that exchanges mental states (i.e., thoughts, feelings, and intentions) in both directions, but researchers in the field tend to focus on one direction for developing their robotic systems. However, both are equally important for human-robot collaboration, I thus introduce recent papers that try to make clear communication in both directions ("*Humans to Robots*" and "*Robots to Humans*") in this section.

a) *User Intention Recognition*: Much of the previous research on LfD for human-robot collaborative tasks has been carried out to recognize "*Social Cues*" such as body posture, facial expressions, direction of gaze, and verbal cues in interactions, since they can give hints to a robot about the goal of the current task for learning. The robots then are able to use these hints to reduce the search spaces to learn the new task for speeding up or to correct their movements [1]. Various techniques are used to recognize human user's intentions like eye-gaze detection [14], speech recognition [15], and motion capture [19], but the most intuitive way to let a robot know about our (humans) thoughts or feelings is probably to use our own (natural) language.

Stefanie Tellex et al. presented a new system for understating human natural language to automatically generate robot control plans corresponding to the natural language commands [20]. They introduced a new probabilistic graphical model called Generalized Grounding Graphs in order to transfer a part of natural language control commands to corresponding groundings like target objects, places, and paths. The proposed approach is based on Conditional Random Fields (CRFs) which is one of popular approaches in natural language processing. They trained the suggested system on a new dataset that they collected from 45 subjects for 22 different

videos using Amazons Mechanical Turk (AMT). This was the annotated dataset of natural language commands that corresponds to correct robot actions. Finally, they were able to interpret high-level natural language control commands such as “Put the tire pallet on the truck” after training their system, and then it generated control plans for the robot.

Recently, Dipendra Misra et al. also introduced a new approach to interpret a user’s natural language instructions to generate robotic actions for manipulation tasks [15]. Their approach considered ambiguity of natural language based instructions since the same instructions can be interpreted differently according to the current situation of a robot like its location and the state of the target objects. For example, an instruction such as “fill the cup with water” can be interpreted by the robot either taking a cup and filling it with water from the tap, or approaching a refrigerator to take a water bottle out from the fridge at first, and then pouring water into the cup with the water bottle according to the environment of the robot.

They handled this ambiguity of robotic instructions and the large variations given by human natural language using a CRF based method with a new energy function that encodes those properties into environment variables for manipulation tasks. Here, the energy function is composed of several nodes and factors that represent natural language (which is converted into a set of verb clauses), environment and controller instruction. To train this model, they first created a new dataset, Verb-Environment-Instruction Library (VEIL)-300, which has six different tasks while considering service robot scenarios like “Making coffee” or “Serving affogato.” The dataset contains natural language commands, environment information, and ground-truth instruction sequences that correspond to the commands. They trained their model on this dataset for mapping the natural language commands to robot controller instructions, and then they showed accuracy of their model, 61.8%, which outperformed all of their baselines on the validation set.

Motion capture is another system that is widely used for making demonstration datasets for teaching robots in the field. Jonas Koenemann et al. presented a real-time motion capture system that enables a robot to imitate human whole-body motions [21]. In this approach, human motions were captured using inertial sensors attached to the human body segments with an Xsens MVN motion capture system. In order to reduce the computational cost, they simplified a human model, so they only considered the positions of the end-effectors (i.e., the position of the hands and feet) and the position of center of mass instead of considering a high number of parameters to represent all joint positions of the body. Then, they applied inverse kinematics to find joint angles given the positions of end-effectors, then generated robot motions while considering finding stable robot configurations instead of just focusing on imitating the human motions directly. They demonstrated their approach with a Nao humanoid robot, and then showed the robot was able to imitate human whole-body motions with consideration for stabilization in real-time.

However, we, as humans, also can catch other people’s

thoughts or emotional states from many other signs like facial expressions, voices or even small body movements even when we do not understand other people’s speaking or we are not able to see whole-body motions of other people so these kinds of signs are also very important and meaningful in communication and widely used by HRI researchers.

Bilge Mutlu showed how embodied cues like facial expressions, gaze, head gestures, arm gesture, social touch, social smile, etc. play important roles in communication through his investigation [22]. He explored research on human communication, and then found that the research provides strong evidence about the hypothesis that embodied cues help achieve positive social and task outcomes in various domains of social interaction such as “Learning and Development” or “Motivation, Compliance, and Persuasion” in human-human communication. Thus, he finally suggested that HRI researchers should study the most effective ways to use such embodied cues for designing social robots while considering the relationship between particular embodied cues and outcomes in order to get similar positive outcomes in human-robot interaction.

His recent work with Sauppe can be a good example which shows the importance of embodied cues for designing human collaborative robots [9]. In this paper, they studied how robots are treated by human co-workers in an industrial setting, while focusing on aspects of the robot’s design and context. The authors found that workers perceive the robots very differently according to various aspects like the physical appearance of the robots or their positions (roles) at their places of work. For example, workers who were supposed to operate the robot treated the robot as their “work partner” or “friend,” while maintenance and management staff just considered the robot the same as other industrial equipment. Another interesting finding here is that human workers felt that the robots had some intelligence because of the robot’s eye movements since it seemed the robots knew what they were doing. Actually, they were pre-programmed movements so that the robots just moved their eyes to follow the trajectory of their arms, however, even though those movements were simple, the movements helped the human workers to understand the status of the robots and their next actions. Thus, it made human workers feel safe when they were working in close proximity to the robots, since they believed the robots were able to convey their intentions through the eyes.

Gesture recognition is also widely used for human-robot collaboration since gestures can be one of the effective communication channels between humans and robots for working together [23]. Various sensors (i.e., a depth camera and a wired glove) and algorithms (i.e., Hidden Markov Models (HMMs)-based algorithms for modeling meaningful gestures and skeletal based algorithms for feature extraction and detection) are used for this line of research.

Jim Mainprice and Dmitry Berenson presented a new framework to recognize humans intentions as early as possible [24]. In this paper, the authors focused on building a framework for early detection of human motion in order to generate safe robot motions when humans and robots are working together

in close proximity. They modeled a human's motion as a Gaussian Mixture Model (GMM) representation and performed Gaussian Mixture Regression (GMR) to predict the human's future motions. Finally, the proposed approach generated robot motions while considering a prediction of human workspace occupancy which is obtained by the swept volume of predicted human motion trajectories. They demonstrated their approach in a PR2 robot simulation after training the framework on the collected human motion demonstrations of manipulation tasks on a table. It showed that the proposed approach was able to take into account the human motion predictions in the robot's motion planner, so the robot could interact with the human co-worker more safely and efficiently in close proximity.

Another interesting keyword that can be used for understanding user's intention is "Affordance." Hema S. Kopula and Ashutosh Saxena presented a new CRF-based approach, called an anticipatory temporal conditional random field (ATCRF), to predict future human activities based on object affordances [25]. Given the current observation of a human user's pose and the surrounding environment of her/him, the goal of the proposed approach is to anticipate what the user will do next. In order to achieve the goal, they first segmented an observed activity in time, then constructed a spatio-temporal graph based on the segmented sub-activities. The graph consists of four types of nodes (human pose, object affordance, object location, and sub-activity), then they augmented the constructed graph with anticipated nodes representing potential temporal segments. The authors demonstrated the proposed approach on the CAD-120 human activity dataset [26] and obtained 2.7% improvement on the state-of-the-art detection results in terms of a success rate. They also reported that this approach achieved 75.4%, 69.2% and 58.1% accuracy to anticipate an activity for times of 1, 3 and 10 seconds before, respectively.

Daqing Yi and Michael A. Goodric presented a new framework for sharing information between robots and humans for task-oriented collaboration [27]. In this work, they considered a cordon and search mission, which is one kind of military tactic for searching out the enemy in an area, as a human-robot collaborative task that has to be solved by a human-robot team. Here, the authors assumed that a team supervisor (normally a human) assigns sub-tasks to his/her robot team members after decomposing the task, then the robot team members are supposed to accomplish these given sub-tasks (i.e., searching a high risk sub-region for their human team members). They suggested the concept of a shared mental model for sharing knowledge about the current situation among all team members (robots and humans), so their framework was presented to help all human and robot team members understand each other correctly according to their task. Understanding all commands from natural language is not easy, but the problem becomes easier in general if all team members know about the goal, so in this paper, the authors suggested to use a task-specific (oriented) grammar for converting a human supervisor's verbal command into a sequence of way points, thus robot team members could understand their given tasks more correctly.

b) *Readable Robot Intentions*: Another direction of LfD research in human-robot collaboration that focuses on communication between robots and humans is designing robot behaviors and functions more carefully in order to show more readable robot intentions.

Breazeal et al. showed that a robot's non-verbal cues are important for building teamwork between humans and robots [28]. In this paper, they recruited a total of 21 subjects then conducted a user study with them about task-oriented interactions between the subjects and the robot Leonardo. Each subject first was asked to teach Leonardo the names of three different colored buttons (red, green and blue) which were located in front of the robot in its workspace, and then checked to see that the robot knew the names and locations of the buttons. After that the subject was asked to guide the robot to turn on all of the buttons. Experimenters recorded videos while the experiment was performed, and then gave a questionnaire to the subject after the experiment. After performing behavioral analysis of the videos, they found that the robot's non-verbal social cues (e.g., changes of gaze direction and eye blinks) helped humans read mental states of the robot and improved human-robot task performance. The self-report results from the subjects also suggested that subjects perceived that the robot was more understandable when the robot showed non-verbal behaviors as well as explicitly using expressive social cues.

Leila Takayama et al. applied animation principles to create readable robots behaviors [29]. In this paper, the authors created a robot animation which shows different robot behaviors according to their hypotheses (H1: showing forethought before performing an action would improve a robot's readability, H2: showing a goal-oriented reaction to a task outcome would positively influence people's subjective perceptions of the robot) and then measured how people described the robot's intentions (before the action is performed) and how people perceived the robot in terms of some adjectives such as appealing and intelligent after conducting a video prototyping study with a total of 273 subjects. They found that people perceived the robot to be more appealing and their behaviors were more readable when the robot showed forethought before taking actions. They also discovered that showing a reaction made people feel that the robot was more intelligent. Even though this research is not LfD based, it shows potential benefits since the animation principles have been verified and successfully used to make a character by connecting its actions in animations. Furthermore, HRI researchers can design robot behaviors and test them using animation instead of building/programming is physical robot to test new designing of robot motions.

Here, it is worth noting that the readable robot behaviors are not always exactly the same as either the optimal behaviors of the robot to achieve its goal or expected robot behaviors that we can predict when we observe the robot operations.

Anca D. Dragan et al. focused on the difference between two types of robot motions (predictable robot motion and legible motion) [11]. They argued that both robot motions are fundamentally different and often show contradictory properties.

Here, the predictable robot motions mean those that match with expected behaviors of observers (humans). On the other hand, the legible robot motions mean those that convey their intentions of behaviors clearly. In this research, the authors formalized legibility and predictability in the context of goal-directed robot motions, then modeled both robot motions based on a cost optimization function which is designed in consideration of the principle of rational action. Finally, they demonstrated that two types of motions were contradictory through their experiments with three characters (a simulated point robot, the bi-manual robot mobile manipulator (HERB), and a human). They found that this difference between two properties derived from inferences in opposing directions, “action-to-goal” and “goal-to-action,” which refer to an observer’s ability to answer the questions: “what is the function of this action?” when she/he observes ongoing robot actions and “what action would achieve this goal?” when the observer knows the robot’s goal, respectively. Their findings through the experiments supported the theory in Psychology that humans interpret observed behaviors as goal-directed actions.

The same authors studied the effect of “*familiarization*” on the predictability of robot motion in their follow-up work [30]. This research originated from the idea of having users learn from robot demonstrations in order to increase their ability to predict robot motions (familiarization) because predictability is one of the keys for building collaborative robots that can work side by side with humans. This research direction is opposite making robot motions more predictable, and it gave us valuable insights about building more natural human-robot collaboration frameworks. They used the same methods that were used in their previous work [30] to generate predictable robot motions, and then conducted a new user study to see the effect of familiarization on the robot motions. They recruited a total of 50 participants via AMT and conducted familiarization tests on two different types of robot motion (natural motion vs. unnatural motion), where the natural motion was defined as motion that is predictable without (or prior to) familiarization. In the experiment, each participant was asked to answer the questions about their predictability of the robot motion before and after exposing the examples of robot demonstration videos. They found that the robot motions became more predictable after familiarization even though the familiarization was not enough for users to identify the robot motions, especially when the robot operated in high-dimensional space with certain complex movements. The authors also reported that familiarization could help humans to be more comfortable to robots and less natural robot motions hindered our ability to predict the motions.

Leah Perlmutter et al. tried to make robots provide their internal states to human users for helping them to understand the robot’s thought and intentions, since we as humans are not able to judge what robots can see, hear, or infer in the same way that we use in human-human communication [31]. In this paper, the authors proposed visualization-based transparency mechanisms rather than developing a human-like verbal (or non-verbal) communication system for robots. The

proposed visualization module is one kind of the add-on tools which could be added on a robotic perception system that consists of three perception components (scene perception, pointing detection, and speech processing) to interpret the robot user’s commands. They conducted a user study with 20 participants with the proposed robotic system, and then investigated the effect of their visualization-based transparency mechanisms. Their findings indicate that visualizations can help users communicate with the robot and understand robot’s abilities even though some participants reported that they still prefer to have human-like transparency mechanisms with robots.

### B. *Interactive/Active Learning*

In recent years, the research of interactive/active learning has received considerable critical attention in the field.

Maya Cakmak and Andrea L. Thomaz introduced this new robot learning method, which is called *Active Learning*, to allow a robot to ask questions to its teacher (a human user) when the robot is unsure what to do next during learning [12]. In this article, they identified three types of queries (label, demonstration and feature queries) for an Active Learning based method in LfD and conducted two sets of experiments with human subjects. The first set of experiments was designed to investigate how humans ask questions in human-human collaboration scenarios with some levels of abstraction of the tasks in consideration of employing the same scenarios for human-robot collaboration. The second set of experiments was designed to evaluate the use of the three types of queries in human-human collaboration scenarios. The authors found that participants perceived the robot as the smartest when it asked questions using feature queries, which is to directly ask about specific features like positions and rotations to manipulate target objects for learning a new task (e.g., “Should I keep this orientation at the start?”). They also reported that this type of query was the most commonly used in human learning (82%) even though this is the most challenging type of query for robots to produce automatically since it requires some level of situation understanding for asking good questions. These findings provide guidelines to design good questions for building robots as an active learner in human-robot collaboration scenarios.

Stefanie Tellex et al. presented an approach for a robot to take advantage of receiving help from its human partner when the robot and the human partner work together for accomplishing a certain task [32]. They used a natural language generation system, which is called inverse semantics, for making a robot that can request help to the human partner in the form of natural language when the robot fails to do some task, so that the robot could recover from the failure based on their help. Since it is impossible to make a perfect robot that never fails, they focused on developing this recovery method based on a natural language generation system for mapping from a desired human helping behavior that the robot would like the human to execute to words in natural language commands. This system was then used for generating requests when the

robot needs assistance. When the robot detects failures using a motion capture system (VICON), their system first represents the failure in a simple symbolic language which indicates the desired human action, and then translates this symbolic representation to a natural language sentence using a context free grammar (CFG) to ask a human for assistance. In this research, the authors demonstrated their approach on a human-robot collaborative task of assembling a table together, and then conducted a user study to evaluate the effectiveness of the proposed approach. The experimental results showed that the proposed approach helped the participants infer the requested action from the robot better than their baselines approaches such as always using a general request (e.g., “Help me”) and generating requests using template based methods (e.g., “Hand me part 2”).

W. Bradley Knox et al. presented a case study of teaching a physically embodied robot by human feedback based on their framework, which is called TAMER (Training an Agent Manually via Evaluative Reinforcement), that they previously proposed for robot learning from human reward [16]. In this paper, the authors focused on teaching interactive navigation behaviors to their Mobile-Dexterous-Social (MDS) robot Nexi using human feedback as the only training resource. There were two buttons for providing positive or negative reward to the robot learner according to its state-action pair, and robot then was able to be trained given the human reward. The authors taught a total of five navigation behaviors such as “Go to,” “Keep conversational distance,” and “Look away” to the robot, then they tested the learned robot behaviors. However, they found that Nexi did not move properly after training due to issues of *transparency*. These transparency issues arose due to mismatches between the current state-action pair of the robot learner and what the human-trainer was observing. The authors pointed out that there were two main reasons for making this confusion: 1) There can be a delay in the robot taking an action, so that the mismatch between human observations and internal states of the robot can happen at this point, 2) The perception system of the robot is not perfect, thus the robot is not able to see some objects around it even if the human trainer can see them. The authors suggested that researchers should address these transparency challenges when they employ a human feedback based robot learning method for teaching a physically embodied robot.

Karol Hausman et al. presented an approach based on the *interactive perception* paradigm which uses robot’s actuators for actively getting more information about the environment (world) when the robot is unsure for making a decision at the moment [33]. They proposed a particle filter-based approach to combine visual robotic perception with the outcomes of the robot’s manipulation actions in a probabilistic way, and the robot then found the best action to reduce uncertainty over articulated motion models given all sensory inputs at the moment. Here, the articulated motion models indicate the possible movements of objects such as certain directions (or rotations) of the objects that can be used for manipulating them. For example, a door of drawers or cabinets has parts that can be

moved (also cannot be moved) for opening/closing it and it can provide useful information to a robot for manipulating the door since the information can be used for reducing the manipulation space. In this work, they considered four types of articulated motion models: rigid, prismatic, rotational and free-body, and then parametrized them with different numbers of variables according to the types. They demonstrated the proposed approach using a PR2 mobile manipulator, and then their experimental results supported that the robot was able to effectively reduce uncertainty over models in four manipulation scenarios (opening and closing of a rotational cabinet door, moving a whiteboard eraser in a straight line, opening a locked drawer, and grasping a stapler on a table), and the robot then selected the best action based on a KL-divergence based information gain approach.

Stefanos Nikolaidis and Julie Shah introduced an interactive training method, which is called *Cross-training*, for improving human-robot teamwork [34]. A human and a robot are supposed to switch their roles during the training phase for learning a new collaborative task by cross-training. This training approach can be considered as a mutual adaptation process. They reported that a human-robot team performance was significantly improved by cross-training for accomplish a collaborative task, a simple place-and-drill task, in their experimental results with human subjects. The authors also showed that participants who iteratively switched their positions with their robot partner, Abbie, perceived the robot much more positively than their comparison group who trained with the robot using standard reinforcement learning methods in the post experimental survey. Their findings suggest that we are able to get better team performance with a robot partner for accomplishing certain tasks together when we switch our role with the robot during training phase in a way similar to human-human team training practices.

### C. Learning of Complex Tasks

Learning complex tasks is one of the most challenging aspects of employing the LfD paradigm in the field. Therefore, to date, there are few studies that have investigated LfD based learning for teaching complex human-robot collaborative tasks to a robot [3]. Most of them used a decomposing method to make a single complex task into multiple relatively easy sub-tasks for training a robot.

Scott Niekum et al. presented a Hidden Markov model (HMM) based method, which is called Beta Process Auto Regressive HMM (BP-AR-HMM), to segment unstructured demonstrations into multiple sub-skills that enable a robot to learn complex demonstrations in a single integrated framework [35]. Here, the authors pointed out four key requirements for robot learning of complex tasks: 1) the robot must have an ability to recognize repeated instances of skills and generalize them; 2) the robot should be able to do segmentation without prior knowledge; 3) a broad/general class of skills should also be identified by the robot; and 4) the robot should be able to represent the skills properly for learning new policies. In this paper, they addressed all of the above requirements using BP-

AR-HMM and Dynamic Movement Primitives (DMPs) which is a framework for representing dynamical systems. They then demonstrated that the proposed approach helped the robot learn a multi-step task from unstructured demonstrations.

Nadia Figueroa et al. also employed BP-HMM based approach for teaching a complex sequential task, pizza dough rolling, to a robot from human demonstrations [17]. In this paper, they first extracted a set of unique action primitives (reach, roll and reach back) and their transition probabilities using an extended version of BP-HMM, and then trained the model on human demonstrations to learn low-level robot control parameters for generating proper robot control commands corresponding to each action primitive. The authors evaluated the proposed framework on the pizza dough rolling task with a real robot and showed that the robot made the pizza dough with consistent shapes and a desired size while their baseline approach showed unstable performance in three different types of dough (very soft, a bit stiffer, and a hard dough) since it used a fixed hand-tuned parameters.

Even though the target scenarios of robot learning in the above mentioned two approaches are not human-robot collaborative tasks, both approaches show the challenges for teaching a robot more complex tasks using LfD based approach and the automatic segmentation methods for handling these issues. However, in order to apply this line of research for human-robot collaborative tasks, a robotic learning system should be able to extract different action primitives which are more related to “interaction” rather than action itself.

Marco Ewerton et al. presented a Mixture of Interaction Primitives for learning multiple interaction patterns between two agents (i.e., a human and a robot) from unlabeled demonstrations [13]. Here, Interaction Primitive (IP) is a framework based on DMPs that was proposed by Heni Ben Amor (who is one of co-authors of this paper) for robot interactive skill learning and this work is follow-up research that overcame limits of the previous approach (IP) for learning more complex tasks and handling various interaction patterns. The main contribution of this work is modeling multiple interaction patterns using Gaussian Mixture Model (GMMs) of Interaction Primitives, so that it enabled modeling nonlinear correlations between the movements of two different agents (a human and a robot). In this work, the movements (trajectories) were represented in the form of the weight vectors, one for each demonstration about a human-robot collaborative task, and they stacked the several vectors for making a probability distribution. After that they trained their model to learn interaction patterns based on the weight vectors that parameterized the trajectories in the demonstrations. They collected a total of 28 pairs of human-robot demonstrations for training the proposed framework, and then trained the robot for selecting the appropriate robot reaction given the observation of the human partner during collaboration. Their experimental results supported that the robot was able to learn and recognize multiple human-robot collaborative tasks based on the proposed approach.

### III. CONCLUSION

In this paper, I presented a survey of robot learning from demonstration (LfD) approaches for Human-Robot Collaboration. LfD is a very attractive research direction for building a collaborative robot since it enables robots to automatically learn a new task from non-robotics experts (end-users). However, it is also challenging because there are common theoretical issues like the *Correspondence Problem*, and the situation becomes more challenging when a robot learns complex tasks. Moreover, researchers should also consider many human-centric issues such as safety, human partner's feelings, and intention for teaching a robot for collaboration with humans. Since the human-robot collaborative task is not a manufacturing task that a robot can perform alone (i.e., painting and assembly), but requires a robot to work side by side as a partner for accomplishing the task, researchers thus must consider the human-centric issues.

The most important key word here is communication because a way to communicate between two agents (a robot and a human) can be very different from a way of communication between people, even though there are a lot of efforts to make this human-robot communication similar to human-human communication. Communication is a bidirectional activity, however a lot of robotics researchers tend to view this activity from one direction. In this survey paper, I thus categorized the LfD based research that focuses on a communication problem into two lines of works according to their research directions and described many interesting findings in the both directions.

Several attempts have been made to use non-verbal cues such as facial expressions, gaze directions, and body gestures in human-robot communication since these signals can give out additional useful information for natural and effective communication between a human and a robot. In addition, some research has been carried out for designing human readable robot behaviors (predictable and legible robot motions) for conveying a robot's intentions during collaborations.

Another interesting line of research in the field is the works which employ an interactive/active based method for robot learning. These studies suggest seeing a robot as an active learner that can ask questions when the robot is unsure what is going on and what to do next. Furthermore, the robot can actively move itself for gathering more information for accomplishing/learning a new task in those kinds of situations.

One of the most difficult remaining challenges in the field is teaching complex collaborative tasks to a robot. Given a demonstration of complex tasks (i.e., assembling a table) that include a number of sub-tasks (i.e., picking-up a part, holding a part, and turning a screw), we want the robot to automatically find the sub-tasks, then generalize and learn them from the demonstrations. Since each teacher (a human partner in common) can have different ways of teaching a robot learner which involve large variations in movements, teaching a robot human-robot collaborative tasks becomes more challenging. Hidden Markov Model (HMM) based approaches are widely used to model dynamics in interaction for learning and they

show some possibilities, but learning complex collaborative tasks still remains open due to the difficulty of the problem, so researchers, as yet, only consider teaching a relative simple task for robot learning.

Recently, deep learning based approaches have been widely used in many applications including object detection, scene segmentation, and learning robot motor control policy for grasping objects [36]. However, only a few previous studies have investigated applying deep learning based techniques for teaching robots human-collaborative tasks from demonstrations. In my view, the main reason is that it is hard to build a large-scale dataset, which is required for training a robotic system to apply deep learning based methods. Different robots have different abilities with different body configurations and different people want to teach the robots different tasks, so all of them make the problem harder.

As we see in the paper, most of research in the field still focuses on making better robotic perception components to understand human's intentions in communication. In my opinion, we apply deep learning techniques to this line of work without difficulty then improve an ability of robots to understand human's intentions. However, making people understand robots is a relatively hard problem because each robot has its own unique robotic system. We can teach robots to mimic a human's motion, facial/body expressions for conveying robot's intentions in the same way as humans using human-human demonstrations in various collaborative scenarios, but I think that there can be better alternative ways for robots to express their intentions and feelings as robots. Moreover, even if human-human interactions can give us valuable insights for building robots that can be used in the same interaction scenarios, simply imitating what humans do may not guarantee the best solution for robot learning of human-robot collaborative tasks. Since each robot has its unique appearance and functions that are usually quite different from humans, researchers need to consider how to transfer the learned knowledge from human demonstrations to each unique intelligent agent. Consequently, the learned knowledge should be adapted to the robot's unique form.

Many possibilities would be open if we consider robots as our active partners like interactive/active learning based research, and then we can take advantage of capabilities of robots themselves for teaching them. However, one drawback of this line of work is it normally considers that human teachers exist in the same place for teaching robots (online learning), but that may not be easy since teaching robots a new task can be a boring and time consuming job.

In this regard, it is time to think about a new learning framework while considering all of the above mentioned challenges and possibilities. As interdisciplinary research, designing robots to collaborate with humans requires a lot of backgrounds, and researchers thus need to collaborate and work more closely with other researchers in different fields to provide the new framework for human-robot collaboration.

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