Can Learning from Demonstration Reproduce Natural and Understandable Movements?

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***Abstract*—There are many factors, such as the dynamic nature of environments, which necessitate that robots should be able to learn new tasks and skills from their end-users. Although some algorithms, like Learning from Demonstration (LfD), have shown promising results in aiding the robotic learning process, other aspects, like their social effects, should be studied to facilitate their use. In this regard, we have conducted a study to determine whether the LfD method can affect the quality of the performance of a task. The parameters we examined in this paper include, but are not limited to, naturalness and understandability of the performed task. Also, to decrease the effect of people's expectations of the robots, we tried to have a reference point because of which the robot performed the pointing action with a simple method (i.e. an Inverse kinematic based method). After using these two methods to teach a robot to point to objects, the participants were asked to fill in a questionnaire regarding those learning methods without knowing which action was performed by the LfD. After gathering the viewpoints of 36 participants, we found that the subjects believed that the LfD method reproduced natural and understandable movements. In a preliminary comparison, while both of the methods were understandable for the participants, the LfD method was found to reproduce significantly more natural tasks than the simpler Inverse kinematic based method. Also, the participants thought/believed that the LfD method was more reliable to teach new tasks, and they expected to see significant differences in the performance of complex high-level tasks learned by these two methods.**

Keywords—Learning from Demonstration (LfD), Human-Robot Interaction (HRI), Social Robot, TP-GMM, Naturalness, Understandability

I. Introduction

New generations of robots are being designed to interact with humans and other robots in dynamic social environments. These robots are being used in the fashion industry [1], educational systems [2], [3], rehabilitation [4], [5], etc. For robots to excel in these environments, they must be able to learn new tasks. While one line of research is investigating new methods of learning, another line should study the impact of those learning methods on the users.

Learning from Demonstration (LfD) is a learning scheme that has received special attentions in recent years. Different methods like the Symbolic approaches [6], [7], Dynamical Movement Primitives (DMP) [8], [9], model mixtures like TP-GMM [10], etc. are being used for this purpose. Although preventing end-users from coding new tasks is the main advantage of LfD [11], its benefits can go beyond this in a social robotics context. As mentioned in [12], although people react to different situations properly, they cannot always explain the details of their reaction; LfD can be used to alleviate this problem because it merely requires people to reproduce a reaction in the desired situation rather than trying to explain the reaction. In addition, [13] mentions that this way of teaching a task is beneficial to both of the learners and the teachers (end-users), as in this method, end-users are able to utilize intuitive way of teaching as they do for humans.

Other than the benefits mentioned in the last paragraph, LfD eventually would reproduce a trajectory of movement variables (e.g., position, orientation, force, etc.) that may or may not be meaningful. Therefore, like other methods, evaluating the social aspect of the reproduced movements seems to be an important step for LfD methods, especially for social behaviors whose ultimate goal is to transfer a message to others. With those in mind, in this paper, we studied whether the Learning from Demonstration method reproduces natural and understandable tasks, as two socially-effective factors. The task about which we have conducted this research was "pointing" as a communicative gesture in which the social aspect of the movement (especially the naturalness and understandability) can broadly affect the quality of the movement.

Communicating with humans is an important feature that sets social robots apart from other robots. This communication can be verbal, such as talking, or non-verbal, such as body gestures. One of the gestures learned from childhood that has a great impact on communication is the act of pointing. In [14], Esteve-Gibert et al. mentioned that pointing and reaching gestures are among the first communicative skills that infants learn. The act of pointing, as an interactive gesture, is a subject of interest to social roboticists. Breazeal et al. [15] examined the effect of this operation on Leonardo, a social robot. According to the study, pointing not only improves the users' communication with the robot, but it also allows them to interact more confidently (because the robot can show the user that it can understand what they mean). Also, Marjanovic et al. [16] cited pointing as a key prerequisite for doing other tasks, such as grasping and moving objects in the environment.

In this paper, we compared a pointing task with two different reproduction methods. In one method, the Arash-2 robot (Fig.

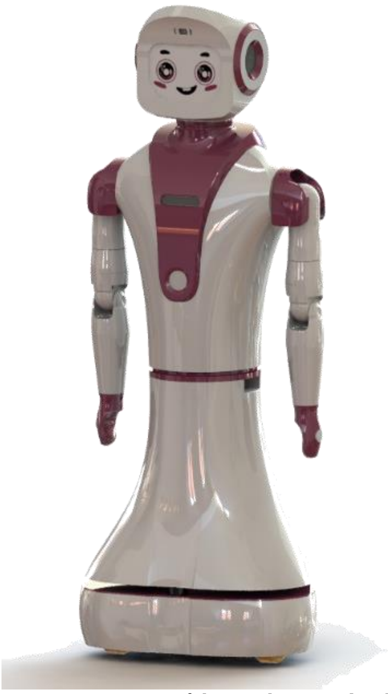


Fig. 1. A picture of the Arash-2 Social Robot.

1) learns to reproduce the task using the Learning from Demonstrations (LfD) method, and in the second method, the task is reproduced with a simple inverse kinematic method (referred to as the simple method) in which the robot moves its arm to align its shoulder with the center of the object it is pointing at. Although the second method is very simple, we needed it as a reference point to be able to compare and evaluate the results from the first method. After the task was performed using the two methods, the participants were asked to rate the robot's movements from different aspects without knowing which method was used. Our hypothesis in this study is that the actions of the robot using the LfD method will be scored significantly better than the simple method.

Section 2 describes the methodology used in this experiment, and the results and discussion of the questionnaires are presented in Section 3. Lastly, Section 4 discusses the conclusions, limitations of this work, and some suggestions for future studies.

II. Methodology

A. Arash-2 Robot

The robot in this experiment is the Arash-2. This robot is the second version of the Arash robot designed and fabricated at Sharif University of Technology, Iran to communicate with children, especially those who suffer from cancer [17]. This social robot has 13 Degrees of Freedom (DoF): four in each arm to let the robot move them freely, two in the neck to allow the robot to see around itself, two in the base to move easily in the room, and one in the waist. Arash-2 has a webcam on its forehead and a Realsense camera in its chest. These sensors let the robot perceive the environment. In this experiment, we use the Realsense camera and the four DoF in the left arm (Fig. 1).

B. Pointing methods

In this study, we compared two different methods of performing the pointing task: first, a simple easy-to-implement method, and second, a computation-intensive LfD-based method.

In the first method, Arash-2 tries to align its pointing arm with a virtual line connecting its shoulder to the target. Therefore, it points to the target with a straightened arm. The main challenge in this method is localizing the target with respect to the robot.

The next method used the TP-GMM algorithm to learn the movement from demonstrations. In the demonstrations, we guide the robot's arm to point to the targets placed in various positions with respect to the robot. We hoped that the robot would learn to appropriately generalize these movements for targets in other positions. The first step in implementing the TP-GMM algorithm (for a detailed tutorial, please refer to [18]) is to define the candidate subspaces (i.e. the task parameters). To do this, we considered two subspaces. The first obvious choice for the goal subspace's location is the position of the target object. The start subspace's location is a virtual point whose location is decided such that the robot is pointing to it initially, and its distance from the robot's shoulder is exactly the same as the target to shoulder distance (this distance was chosen to keep both subspaces' features in the same range). After choosing the subspaces' location, it is essential to define the features we want to describe movements from the perspective of those subspaces. In this project, we used new kinds of subspaces. Instead of using spatiotemporal features, we used six features from each subspace in the learning process: time, the angle between the forearm and a line connecting the elbow to the center of the subspace, and four sigmoid-like features limiting the robot's joint angles to feasible values (for each degree of freedom, superposition of two sigmoid functions were used. If the joint's angle was in the feasible space, the output of this function would be two; otherwise, it would be one (3rd-6th features in Eq. 2) The feasible space of each degree of freedom is defined as (1):

$$\theta_{i_{min}} < \theta_i < \theta_{i_{max}} \tag{1}$$

where θ_i is the value of one of the arm's joints and $\theta_{i_{min}}$ and $\theta_{i_{max}}$ are the minimum and maximum possible value for the joint, respectively. With similar terminology, the features used in each subspace (i.e. the j-th subspace) are (2):

$$Z^j = \begin{bmatrix} t \\ \theta_0^i \\ \frac{b}{1+\exp\left(a\times\left(-\theta_1+\theta_{1_{min}}\right)\right)} + \frac{b}{1+\exp\left(a\times\left(\theta_1-\theta_{1_{max}}\right)\right)} \\ \frac{b}{1+\exp\left(a\times\left(-\theta_2+\theta_{2_{min}}\right)\right)} + \frac{b}{1+\exp\left(a\times\left(\theta_2-\theta_{2_{max}}\right)\right)} \\ \frac{b}{1+\exp\left(a\times\left(-\theta_3+\theta_{3_{min}}\right)\right)} + \frac{b}{1+\exp\left(a\times\left(\theta_3-\theta_{3_{max}}\right)\right)} \\ \frac{b}{1+\exp\left(a\times\left(-\theta_4+\theta_{4_{min}}\right)\right)} + \frac{b}{1+\exp\left(a\times\left(\theta_4-\theta_{4_{max}}\right)\right)} \end{bmatrix} \tag{2}$$

TABLE I. THE QUESTIONNAIRES STATEMENTS. EACH PARTICIPANT SCORED THESE STATEMENTS FOR THE TWO LEARNING ALGORITHMS.

# item	Question	Addressing features
1	Robot's pointing was totally understandable.	Understandability
2	Robot's pointing behavior was the same as a human.	How natural was the pointing
3	Robot used all of its physical capability during the pointing.	If the robot performed the action with all expected elements
4	With this method, I think I can teach the robot to move from its initial point to a desired point (i.e., a simple low-level and simple high-level task).	Generalizability of the learning method.
5	With this method, I think I can teach the robot how to write its name (i.e., complex low-level and simple high-level task).	Generalizability of the learning method.
6	With this method, I think I can teach the robot how to play with a balloon (i.e., simple low-level and complex high-level task).	Generalizability of the learning method.
7	With this method, I think I can teach the robot how to cook (i.e., complex low-level and complex high-level task).	Generalizability of the learning method.
8	I think this learning method is very complex.	How people relate the observed performance with the mathematics requirement behind each algorithm.

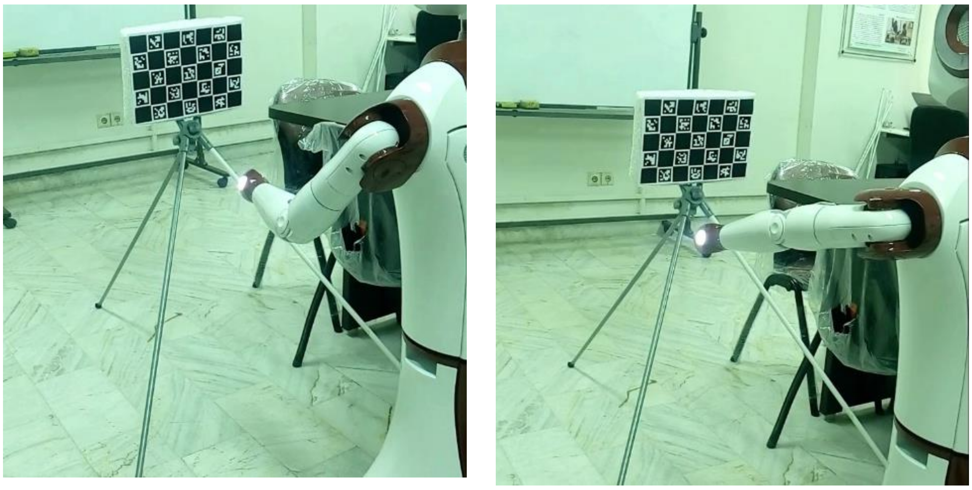
where θ_0^i is the angle between the forearm and the virtual line as described above, θ_1 is the rotation angle of the shoulder, θ_2 is the abduction angle of the shoulder, θ_3 is the spine angle of the elbow, and θ_4 is the rotation angle of the elbow. Also, a and b are scaling factors used to avoid numerical problems during the learning and reproduction phases.

One challenge in this method is the nonlinear nature of these features, which limits the use of TP-GMM. To tackle this problem, we have modified the TP-GMM method with an idea mentioned in [19] to exploit nonlinear features. The full details of this method are beyond the scope of this paper.

C. Participants and the assessment tools

Thirty-six people participated (mean age: 27.75 years, SD age: 8.8 years) in this experiment. The exclusion criterion, those who were not familiar with robotics, was used to select the participants. Moreover, although age, gender, and education were also asked, we did not consider these parameters in this study.

To compare the two reproduction methods, two questionnaires were prepared to evaluate the different aspects of learning (TABLE I). Four of these statements (i.e., Q1-03



a b

Fig. 2. Snapshots of the videos sent via social media showing the algorithms used for the robot's pointing to a target: a) the LfD method, and b) the simple method.

TABLE II. THE RESULTS OF THE PAIRED T-TESTS ON THE PARTICIPANT'S SCORES OF THE . THE SCORES ARE OUT OF 5. P-VALUES LESS THAN 0.05 ARE SHOWN IN BOLD.

No.	Question No.	Mean *(SD)* LfD Method	Simple Method	T-Value	P-Value
1	Q1	3.639 *(1.073)*	3.333 *(1.095)*	1.87	0.07
2	Q2	3.556 *(0.939)*	2.750 *(1.156)*	4.14	**0.000**
3	Q3	3.444 *(1.027)*	2.778 *(1.124)*	3.01	**0.005**
4	Q4	3.806 *(0.951)*	3.528 *(0.878)*	1.71	0.096
5	Q5	3.250 *(1.131)*	2.889 *(1.090)*	1.55	0.130
6	Q6	4.222 *(0.681)*	3.750 *(0.967)*	2.69	**0.011**
7	Q7	3.222 *(0.959)*	2.583 *(1.079)*	3.26	**0.002**
8	Q8	3.333 *(1.287)*	2.750 *(1.228)*	3.240	**0.003**

and Q8), which were chosen from the UTAUT [1] [20] questionnaire, were about the apparent feature of the executing action, i.e. pointing. The other four statements (i.e., Q4-7) were made by ourselves to get a preliminary insight into the people's opinion about the generalizability of the methods and design more sophisticated experiments to evaluate this parameter in future studies. Participants were asked to score the statements of TABLE I according to a 5-point Likert scale (i.e., 1: totally disagree, 2: disagree, 3: neither agree nor disagree, 4: agree, and 5: totally agree) [21], one time for the first algorithm and another time for the second method. Due to the Covid-19 pandemic, these questionnaires were attached to a video (Fig. 2), including six pointing actions (three for each method), and sent to the participants via social media instead of calling people to come to the Lab. To avoid any biases that may be caused by the sequence of the videos, half of the participants were randomly chosen to be shown videos of the LfD method first, while the other participants were shown the second method first (i.e., the counterbalanced condition).

III. RESULTS AND DISCUSSION

After watching the videos of the robot's performance sent through social media, the participants filled in the provided questionnaires. In order to ascertain whether there was a significant difference between the participants' viewpoints about the robot's performances in the two modes of the pointing tasks, paired t-tests were performed on the questionnaires' results (TABLE II).

TABEL II shows us that the LfD method received positive feedback (>3) from the participants, and as a preliminary comparison with the reference point (i.e. the simple method), we see that the mean values for the LfD method were higher than the simple method in all of the questions. Also, for all questions (except Q1, Q4, and Q5), the p-values are less than 0.05, meaning there was a significant difference between the observed results between the performances of the Arash-2 robot using the LfD method and the simple method. As mentioned above, this comparison was done to have a reference point and get a glimpse of people's opinions, not to any show benefit of the LfD methods over the IK method.

As the main finding of this study, we concluded that although people found that the results of the LfD method were more understandable, the difference between these two methods regarding this item was not significant. However, the LfD method's reproduction was considered to be significantly more natural than the simple one.

Regarding Questions 1-3, which were about the actions performed by the robot, cumulatively, the Cronbach's alpha of Questions 1-3 for the LfD method and the simple method phases were 0.73 and 0.69, respectively, which indicates acceptable levels of internal consistency for our scales regarding the designed questions. Moreover, although the robot was able to perform the pointing actions using the simple method, what we observed indicated that the participants did not believe in the robot's intelligence level or that it systematic learned knowledge using this algorithm (i.e., mean values of 2.95 (<3) out of 5 in the first three questions). Therefore, albeit the fact that the second method was conducted for a preliminary comparison, we can deduce that it is worth making the effort to develop appropriate algorithms to empower the social aspects of learning methods as well as their learning schemes. The overall mean value of the LfD method in the first three questions is 3.55 (out of 5), which indicates the participants' perceived an understandable level of the Arash-2 robot's intelligence and considered its movements to be natural as well as using its capabilities. However, there remains room to improve the algorithms for the robot's learning as well as the robot's design/movement restrictions. In [22], it is also mentioned that there are lots of other features required to make a social robot satisfactorily behave highly sociable/alive. Regarding the first three questions, the greatest differences between the two pointing algorithms were observed in Q2 and Q3, which show the obvious differences in the naturalness and physical capacities used in pointing. This observed dissimilarity was expected because the LfD approach utilized all the degrees of freedom of the arm as opposed to only two in the IK equations for simple method; if the active joints of the robot were more than two ones, we would have an infinite number of solutions for the IK equations. Since we did not have any criteria to choose between those solutions, only two degrees of freedom of the shoulder were used. On the other hand, the criteria could be established from demonstrations for the LfD method.

Next, Questions 4-7 were analyzed to investigate the participants' viewpoints regarding the performed algorithms' generalizability potentials to other applications. Based on TABLE II, we observed two interesting points that should be evaluated in detail in future studies. The first point is that although people thought/believed that the LfD method would

[1] The Unified Theory of Acceptance and Use of Technology (UTAUT)

perform better than the simple one (higher mean values for the LfD method) in all four questions, no significant difference was observed between these two methods for the simple high tasks (i.e., moving between two points and writing its name). However, for complex high-level tasks (i.e., playing with a balloon and cooking), the participants thought/believed that the LfD method was significantly more generalizable than the simple one. This is a preliminary observation and should be investigated more in future studies. However, as a first supposition, this may have been caused by the fact that pointing is a simple high-level task, and since participants found both of the methods understandable (Q1), they thought/believed that both methods could be used for teaching other simple high-level tasks. The second interesting point is that the highest mean scores for the LfD method in questions 4-7 were observed in questions 4 and 6, both mentioned simple low-level tasks (3.806 and 4.222, respectively). This could be a preliminary signal that (after observing the robot's pointing abilities,) the participants believed the LfD algorithm was more generalizable to reproducing other simple low-level tasks (e.g., moving in the room or playing with the balloon) than complex ones (e.g., writing or cooking). Confirming this hypothesis will need more experiments and deeper scientific analysis. Also, Cronbach's alpha for Questions 1 and 4-7 are 0.67 and 0.74 for the LfD method and the simple method, respectively, which show acceptable internal reliability in this study.

Regarding Question 8, the participants rated the complexity level of the robot's calculations of the LfD algorithm, "medium (i.e., 3.33)" (while having significant differences with the simple) for general robot's learning purposes. Although the mathematics behind the proposed algorithm is complex, the participants' mean result in Q8 was probably due to the high expectations of ordinary people for robots. Similar observations are presented in [23].

IV. Conclusion

This research aims at studying the social aspects of Learning from Demonstration methods. For this, the Arash-2 robot was taught to perform a pointing act, a socially important task, using two different methods. One of the methods was our modified TP-GMM LfD-based approach, while the other one was a simple method in which the joint trajectories were calculated by inverse kinematics. The second method was used to have a reference point to allow the evaluation of the participants' opinions; therefore, this comparison does not apply to all LfD and IK methods. After the robot was able to perform the task, 36 participants, who were unfamiliar with robots (our exclusion criteria), were asked to score different aspects of its performances. According to the results gathered from the questionnaires, the LfD method was able to reproduce amenable movements considering all the desired features, and although the participants did not see any significant differences in the understandability level of these two methods, they found that the LfD method's reproduction is significantly more natural than the simple one. Also, considering if one can teach new skills to the robot with the presented algorithms, people were asked to score their opinions about four tasks. Although the participants were optimistic about both algorithms, they thought that the LfD method was more reliable than the simple method for complex high-level tasks. However, they did not expect any significant differences between the two methods for simple high-level tasks.

There were several limitations to this work. First, our participants were limited to those who had access to social media due to the Covid-19 pandemic. This limitation may display a bias since we only collected the opinions of people who were familiar with technologies. Next, according to the results of [24], after watching the robot's performances on videos, participants might not be able to as insightfully evaluate all the features as they would in person, and the robot's performance may be viewed differently from a situation in which people can physically interact with the robot. In addition, this limitation restricted us from assessing other features of Arash-2. Third, due to the lack of similar papers investigating Learning from Demonstration approaches on the naturalness of robots' behaviors, such as pointing or other social tasks, in the literature, we could not systematically compare our results to similar studies. Lastly, the simple method we used as our reference point was a strawman, and a more sophisticated method may be needed to make a definitive comparison. To counter this limitation, there should be a benchmark or a reference method we could use to compare our results. A study with a more detailed comparison of the learning algorithms and without these limitations needs to be done in the future.

V. Acknowledgment

Author Alireza Taheri has received a research grant from "Sharif University of Technology" (Grant No. G980517). We also appreciate "Dr. AliAkbar Siasi Memorial Grant Award" for the complementary support of the Social & Cognitive Robotics Laboratory.

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