

# Social Robot Learning from Demonstration to Facilitate a Group Activity for Older Adults

Wing-Yue Geoffrey Louie, *IEEE Student Member*, Francis Despond, and Goldie Nejat, *IEEE Member*

*Abstract*— With a rapidly aging population, the demand for long-term care services is also significantly increasing. However, services such as cognitively and socially stimulating group activities for residents are neglected due to the lack of care staff. The objective of our research is to develop socially assistive robots in order to autonomously facilitate such cognitive and social interventions. In this paper, we present the development of a novel system architecture for a social robot to learn from non-expert demonstrators (e.g. care staff) to facilitate group activities with multiple residents. A demonstration from learning approach is used, where the demonstrator demonstrates the facilitation of a group activity using an activity simulator that models the social robot, the users, and the activity itself. The mapping between the activity states and the robot's behaviors are then learned from the demonstrations using a decision-tree based activity learning system. System performance experiments were conducted using the system architecture with the robot Tangy to first learn the cognitive and social group activity of Bingo and then use the learned activity to physically facilitate Bingo games with multiple users. The results showed the approach was able to accurately and efficiently learn the new Bingo activity.

## I. INTRODUCTION

It is projected that by 2050 the proportion of the world population 60 years or older will more than double from 841 million in 2013 to 2 billion [1]. This demographic change will lead to an increase in demand for long-term care homes and services due to the natural decline in social, cognitive and physical capabilities of aging older adults [2]. However, long-term care homes are already understaffed and unable to handle all the services needed by older adults [3]. As a prime example, it is already a major concern among healthcare professionals that services such as cognitive and social activities for residents in long-term care facilities are being neglected [3],[4]. Numerous studies have demonstrated the importance of such activities which include both informal (e.g. conversations with staff, family and friends) and formal social leisure activities (e.g. participation in group recreational programs) in the daily lives of older adults. They have found that these activities are important to protect

residents' cognitive health as well as mitigate the effects of functional limitations, perceptions of disability, and depressive symptoms [5].

With respect to formal group activities, currently, social robots are being developed and implemented successfully in long-term care homes to facilitate group recreational activities including Bingo and Hoy [6],[7], sing-alongs and logic games [8], and ball throwing games [9]. The majority of these robots are either teleoperated by a human operator or not fully automated, with the exception of our socially assistive robot Tangy which can autonomously facilitate Bingo games by calling out numbers, sensing players and Bingo cards, and identify user assistance requests [6].

A recent study conducted by our research group investigated the impressions and design considerations long-term care residents, family, and healthcare professionals had on our robot Tangy facilitating the group leisure activity of Bingo [10]. The majority of participants wanted to see the robot facilitate a number of group activities in addition to Bingo including sing-alongs and trivia. Furthermore, they suggested that additional activities could be included by staff after the robot was deployed in the long-term care home. However, current social robots are limited to a set of a priori known activities that have been previously programmed by human experts. Hence, the aforementioned request presents a new challenge: instead of having a limited set of a priori programmed group activities, robots should be capable of learning new activities while deployed in long-term care homes from non-expert humans in order to adapt to the needs of the home.

This research focuses on designing socially assistive robots capable of autonomously facilitating group social leisure activities for residents in long-term care facilities to improve their overall cognitive capabilities and to expand their social networking opportunities. Our goal is to design robotic technology that is easy to use, acceptable, and adaptive to the long-term care settings that the robots are deployed in. Therefore, we aim to develop robots capable of learning new stimulating group activities from non-expert users (such as staff) and facilitating these learned activities autonomously with residents.

In this paper, we present a demonstration learning system architecture for Tangy in order for the robot to be able to learn new group activities when needed from demonstrations conducted by non-experts. Namely, the system architecture has a learning system to obtain a control policy (activity state to robot behavior mapping) from demonstrations conducted by a non-expert in a simulator. The policy is then used by the physical robot to facilitate the learned group activity with a group of users in a real environment.

This research was partially supported by the Natural Sciences and Engineering Research Council of Canada (NSERC), Dr. Robot Inc., and the Canada Research Chairs Program (CRC).

W. G. Louie, F. Despond, and G. Nejat are with the Autonomous Systems and Biomechanics Laboratory in the Department of Mechanical and Industrial Engineering at the University of Toronto, 5 King's College Road, Toronto, ON, M5S 3G8 Canada. (e-mail: Geoffrey.louie@mail.utoronto.ca; Francis.despond@mail.utoronto.ca; nejat@mie.utoronto.ca)

## II. RELATED WORK

Robot learning allows a robot to learn in an on-line manner primitive actions or tasks, where the latter consists of a series of actions. Three main methods have been used to teach a robot: 1) Learning from Demonstration (LfD), 2) Active Learning (AL), and 3) Mixed Initiative (MI) Learning.

LfD allows a robot to learn by observing a teacher while he/she demonstrates the specific task or action [11]. This method has been used to teach robots to dance [12], implement certain arm motions [13], and the pick-and-place of objects [14]. For example in [12], the Robota doll robot was taught different dance patterns using its head and arms, as well as keyboard key labels for the dance patterns. Infrared sensors on the teacher captured the necessary arm and head movements to provide to Robota to mimic. After the dance pattern was completed, a label via a single key input on a keyboard was provided by the teacher. A second scenario was implemented where the robot was taught a combination of keys as the sentence label to describe its actions as well as its perceptions of touch on its different body parts. A winner-takes-all network was then used to map the actuator joints and perceptions of touch (via switches) to the labels. Experiments determined that the robot was not only able to learn explicit associations but implicit ones as well, for example, concepts of individual words like arm, foot, left, right could be understood by teaching full sentences.

In [13], the humanoid robot Simon was taught arm motions using a Keyframe LfD approach which broke down the overall skill to learn into smaller keyframes that were demonstrated. A Gaussian Mixture Model was used to learn an arm motion path. Experiments were presented with 34 teachers teaching the robot various motions such as saluting and inserting a block into a hole using kinesthetic teaching. Performance study results comparing keyframe LfD to trajectory learning LfD (where the skill was not broken down) found that keyframe LfD reduced unintentional movements, however, a single demonstration by the teachers was enough to teach the skill using trajectory learning LfD.

AL has also been used to teach a robot to label objects [15]. AL differs from LfD in that after every step throughout the teaching process, a robot can query the teacher about the task or action being learned [15]. In [15], different active learning methods were compared in teaching the Simon robot labels for a combination of simple shapes, for example, a triangle on a square was labeled a house. A query-by-committee approach was used as the active learning method. Experiments with 24 participants were presented and compared with different conditions for robot queries as well as the case where there were no robot queries. The results showed that AL required less time and number of steps than the other methods to teach the labeling of a combination of simple shapes.

MI Learning is an extension of AL in that during learning, a robot can also query a teacher, however, only when certain conditions are met, e.g. reaching an unknown state [15]. The approach has been used to teach robots to turn on a series of lights [16], learn and grasp objects [17], as well

as to learn body movements [18]. In [16], the Leo robot was trained by a human instructor through voice commands to turn on and off LEDs using colored buttons. A Bayesian likelihood method was used during learning to determine the best action for the robot. When Leo was asked to execute a task, it determined a confidence value for each set of known actions to determine the best action. If the confidence for the best action was too low, it would express tentativeness by glancing at the teacher and the object while performing the action. Once Leo finished an action it would lean forward and perk its ears up for feedback on the task, which is provided via voice commands from the teacher. This learning approach was successful in communicating the robot's internal states to the human teacher through facial expression throughout the interaction. In [18], the robotic dog Aibo used a combination of LfD and MI learning, defined as dogged learning, to learn how to mirror the motions of its tail to its head. Using Locally Weighted Projection Regression as the learning algorithm and preprogrammed controllers in the place of a human demonstrator, the robot was taught via kinesthetic tele-operation to have its head movements mirror the movements of its tail. Experiments using two teachers who demonstrated different motions to the robot showed that the robot was able to merge these behaviors into a single task. The learning approach was also successfully implemented for a ball seeking task.

The aforementioned work has verified that robots can effectively learn a priori unknown tasks using different learning methods. With respect to social HRI, the demonstrations have used natural communication between a robot and a human teacher to achieve task learning, e.g. dialogue systems using verbal commands from the demonstrator. However, for the majority of applications, the task that the robot was learning to implement itself was not necessarily social and the intended application was with only one person after learning was completed. Our problem differs in that we aim to have the socially assistive robot Tangy learn a social activity that needs to be autonomously facilitated with a group of older adults.

## III. THE SOCIAL ROBOT TANGY

Tangy is a humanoid robot with a human-like upper torso and a differential drive mobile base, Fig. 1. Namely, Tangy has a six degree of freedom (DOF) animated head with two DOF for nodding and shaking, two DOF for each individual eye to pan left and right, one DOF for tilting the eyes up and down together, and one DOF for opening and closing the mouth. Mounted on the torso are two six DOF arms that allow Tangy to perform arm gestures. Each arm has two DOF joints in its shoulder, elbow, and wrist as well as a two DOF gripper. Tangy communicates verbally using a synthesized female voice. Tangy's chest mounted tablet is used to display activity related written messages and images. Tangy obtains information with respect to the activity and its environment using a combination of sensors including a laser range finder, two 2D cameras and an IR camera. The robot is also capable of autonomously navigating in an indoor environment using the ROS navfn planner [19].

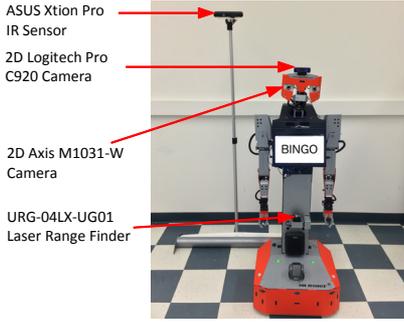


Figure 1. The social robot Tangy.

#### IV. DEMONSTRATION LEARNING SYSTEM ARCHITECTURE

The objective of our activity learning scenario is to have a non-expert human demonstrator demonstrate a social group activity to Tangy using an LfD approach. Since we are focusing on task-level learning [16], Tangy has a set of known behaviors and the goal for the demonstrator is to teach the robot a new task that is not known a priori using these behaviors.

Our proposed system architecture for Tangy is presented in Fig. 2. For robot learning, an activity simulator is used to represent the activity scenario including the robot and the users (e.g. the group of residents). We have chosen to use a simulated environment representation of the activity in order to improve the efficiency of learning and reduce demonstrator fatigue [20]. Furthermore, we can train the robot without having to subject the group of elderly users to long training sessions. The demonstrator controls the robot's behaviors during learning by using speech input and a graphical user interface (GUI) to observe the world state (i.e. defined to be a function of the robot, users and activity models) in real-time. Once an activity from start to end is demonstrated, the sequence of executed behaviors and their corresponding activity states are passed to the activity learning module. This is known as the demonstration trajectory. The activity learning module then learns the policy (activity state-behavior mapping) for the activity. The learned policy is then used by the interaction system to implement Tangy's physical behaviors in the real world using sensory information regarding the world state parameters during a robot facilitated social group activity.

##### A. Speech Identification

The demonstrator uses voice commands to provide the sequence of activity behaviors needed for Tangy to complete the activity. Speech identification is achieved by using the Pocket Sphinx speech decoder [21] to match words in the decoded utterances to keywords associated with known robot behaviors. Namely, Pocket Sphinx passes the utterances into the acoustic model. The acoustic model labels the phonemes using a Hidden Markov Model and then matches the phonemes to words before being passed through the language model, which determines the sequence of words. The sequence of words are then matched to the robot behavior keywords and the demonstrator is prompted on the GUI to verify if the identified robot behavior command is correct prior to being sent to the activity simulator module. Namely, the user is displayed a message on the GUI depicting the

behavior command identified by the speech identification module and prompted to verify if the identified command is correct by typing yes/no on a keyboard.

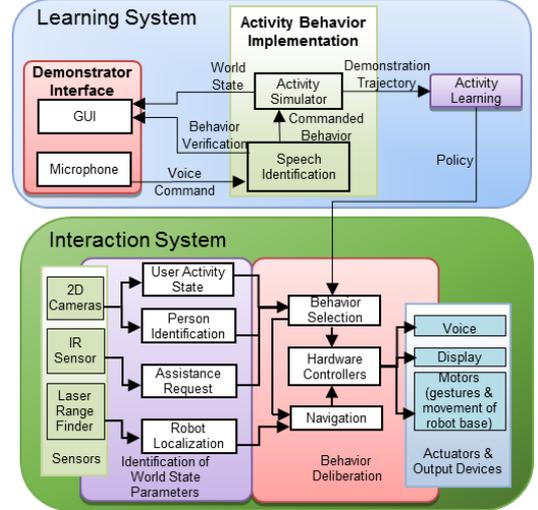


Figure 2. System Architecture for Activity Learning and Implementation.

##### B. GUI

The GUI illustrates the world state provided by the activity simulator. Namely, the robot and users are depicted as virtual agents and their behaviors are shown in real-time on the screen as the world state is updated based on the demonstrator's voice commands.

##### C. Activity Simulator

The Activity Simulator module consists of models for the robot,  $R$ , the activity,  $A$ , and the group of users,  $U$ .

###### 1) Robot Model

The robot is modelled as a simulated agent with a set of known primitive behaviors,  $B = \{b^1, b^2, \dots, b^m\}$ , where  $m$  is the total number of behaviors. These discrete primitive behaviors are defined to be a function of robot actuator positions ( $\theta$ ), speech ( $sph$ ), and visual content ( $img$ ):  $b^i = f(\theta^i, sph^i, img^i)$ , where  $i$  is a primitive behavior.

###### 2) User Model

The multiple users in the group activity are modelled as a set of users,  $U = \{u^1, u^2, \dots, u^n\}$ , where  $n$  is the total number of users participating in an activity at one time. Each user,  $u^r = \{ID, s_{ua}, s_h, l\}$ , is defined by: 1) his/her unique identity,  $ID$ , e.g. his/her name; 2) the state of the activity for this particular user,  $s_{ua}$ , e.g. winning a game; 3) user assistance request state,  $s_h$ , e.g. the user requests assistance with the activity from the robot; and 4) user location,  $l$ , the 2D location within the activity room that user,  $r$ , is located.

###### 3) Activity Model

The overall activity is modelled as a set of discrete stages (e.g. start, facilitate, help, socialize, and end),  $S_a = \{s_a^1, s_a^2, \dots, s_a^g\}$ , where  $g$  is the total number of discrete stages that occur during the entire activity. Each stage, referred to as an activity state, is a set containing a specific instance of discrete time step,  $k$ , and user assistance request state and user activity state for all players,  $s_a^p = \{k, s_{ua}^{1,2,\dots,n}, s_h^{1,2,\dots,n}\}$ , where  $p$  represents a specific discrete activity state.

The aforementioned models are updated after each behavior command is received from the demonstrator. The sequence of behaviors to complete the overall activity is used to define the Demonstration Trajectory.

#### 4) Demonstration Trajectory

A demonstration trajectory can be represented as  $T = \{b^1, s_a^1\} \rightarrow \{b^2, s_a^2\} \rightarrow \dots \{b^j, s_a^j\}$ , where  $j$  is the total number of state-behavior steps required for the complete demonstration. After the demonstration of the activity is completed, the demonstration trajectory is provided to the activity learning module.

#### D. Activity Learning

The C4.5 decision tree classifier [22] is utilized to learn the state-behavior mapping using the demonstration trajectory as training data. We use the C4.5 decision tree classifier as it can account for incomplete data and prevent overfitting a model by pruning the decision trees. In general, the C4.5 decision tree classifier uses a heuristic, one-step look ahead (hill climbing), non-backtracking search through the space of all possible decision trees [22]. Namely, in our learning scenario the decision tree classifier generates all possible decision trees from the demonstration trajectory. It then searches through the generated trees to identify the decision tree that best models the demonstration trajectory. Herein, robot behaviors  $b^i$  are the labels and the activity states  $s_a^p$  are the attributes being classified. Each unique path in the decision tree defines the decision rules for a robot behavior to be executed in a specific activity state. Thus, the final learned decision tree model is the policy,  $\pi(s_a^p) = b^i$ , which provides a state-behavior mapping for the demonstrated activity.

#### E. Interaction System

Once the policy has been learned and training is over, the learned policy is then used by the interaction system to control Tangy's physical behaviors during the group activity. The activity state representation can be obtained using the robot's available sensors to identify the necessary model parameters via the World State Parameters modules.

### V. LEARNING TO FACILITATE BINGO GAMES

We have implemented our system architecture for Tangy to learn and implement the group activity of Bingo. We have selected Bingo as it has proven to be effective in promoting social bonding among residents and is effective in training cognitive skills including recognition, recall, and visual search [23]. The task was not known a priori by Tangy.

Tangy has a known set of prior primitive behaviors (we obtained from our previous work [6]) which are presented in the fourth column of Table I. These behaviors include: greeting players, Bingo number calling, helping them play the game (e.g. requesting them to mark called numbers on their specific cards and celebrating when they have Bingo), telling jokes, navigating in the environment and valediction.

The set-up of the Bingo game consists of four players sitting at a table facing Tangy with their own Bingo cards placed on top of the table in front of them, Fig. 3(a). Each

card has a unique grid of 5x5 numbers randomly selected from 1-75. Players are also provided with red circular markers for marking the numbers on their cards. During a Bingo game, Tangy stands at the front of the room and calls out Bingo numbers in a random order, while the players mark these numbers on their cards if they have them. Players can request Tangy to come over to them to provide help by pressing a button on an assistance request device. If the card is outside of the robot's field of view (fov) when it is providing assistance, Tangy can request the player to move the card closer. A player wins Bingo if he/she correctly marks five numbers in a row, column, or diagonal on his/her card. The first four columns of Table I present the expected robot behaviors for the Bingo game based on a given activity state, as well as the user assistance request state and user activity state for all players that the activity state is based on.

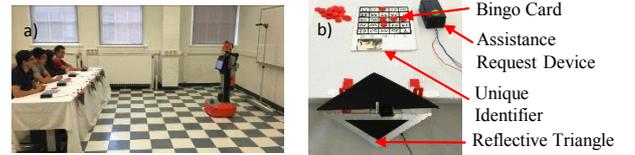


Figure 3. a) Bingo game scenario; b) Player's assistance request device and Bingo Card.

#### A. Bingo Simulator

The activity simulator for Bingo has been designed to represent the aforementioned game scenario. Through the GUI, the demonstrator can observe the world state and in turn control the robot's primitive behaviors through voice commands. This allows for simple demonstration for non-expert demonstrators. Numerous Bingo games with different sequence of events (randomly determined) can be played using the simulator. The simulation environment is presented in Fig. 4.



Figure 4. Activity Simulation during a demonstration of a Bingo game: a) robot calls a number and player requests for assistance; b) robot requesting a player to remove marker from uncalled number.

#### B. Bingo Interaction with Tangy

In the real-world implementation of the Bingo activity, Tangy utilizes its various sensors to determine the world state parameters. Namely, the robot identifies the following state parameters: 1) its own location in the environment using its on-board laser range finder and optical encoders, 2) the player identities, 3) the users' activity states, and 4) assistance requests from the players. Robot localization is achieved using the on-board laser range finder and optical encoders. Namely, the Gmapping technique [24] is used to map the room that Tangy facilitates an activity in. An adaptive Monte Carlo technique [25] is then used to localize Tangy within the mapped room. Tangy uses one of the 2D cameras in its eyes to identify a player. Namely, the OKAO™ Vision software library [26] is used to recognize players based on their facial features. The state of an activity

for a particular user is identified using the 2D camera mounted on Tangy’s head to identify and assess the marked numbers on a player’s Bingo card, Fig. 3(b). A Speeded-up Robust Features (SURF) [27] based detection method is used to identify a unique identifier placed on each player’s card. A Hough transformation [28] based method is then used to identify Bingo numbers a player has marked and his/her specific user activity state. In cases where a card is outside of Tangy’s fov, the user activity state is considered occluded. An IR camera placed in the environment behind Tangy is used to capture 3D point clouds of the environment and recognize IR reflective triangles that are exposed when a player presses his/her button on the assistance request device, Fig. 3(b). A Hough transformation [28] based method is used to identify the triangles in IR images. The location of the player who requested assistance is determined by identifying the average position of the corresponding IR triangle in the 3D point cloud of the environment. More details about Tangy’s sensors and detection methods can be found in [6].

## VI. EXPERIMENTS

The performance of the system architecture for learning and implementing Bingo games was investigated by determining the following: 1) the minimum number of Bingo demonstrations required to learn the activity policy, 2) if different demonstrators have any effect on the learned policy, and 3) the performance of the learned policies when implemented. The non-expert demonstrators who participated in the experiments were university students with no previous robot teaching experience.

*Scenario 1* - In this scenario, one non-expert demonstrator demonstrated the group activity of Bingo to Tangy through a total of five demonstrations. We then incrementally provided demonstrations to the activity learning module until we identified the minimum number of activity demonstrations required to learn the expected policy.

*Scenario 2* - In this scenario, five different non-expert demonstrators demonstrated the Bingo activity to Tangy a total of three times. The learned policies from each demonstrator were then compared.

*Scenario 3* - In this scenario, we used the policy learned from one of the demonstrators in Scenario 2. Namely, we applied the policy in the interaction system for Tangy to physically facilitate twenty Bingo games with four players. Players were university students (different from the demonstrators).

### A. Results

It took on average 9.6 minutes to demonstrate a complete Bingo game to Tangy. An average of 62 executed robot behaviors were implemented by each demonstrator during the Bingo learning stage.

*Scenario 1- Results:* It was determined that three demonstration games were needed as the minimum number of demonstrations required to learn the Bingo game policy.

*Scenario 2 – Results:* As expected, the exact same Bingo activity policy was obtained by the five demonstrators.

*Scenario 3- Results:* The results of the Bingo game interactions are presented in Table I and Fig. 5. Tangy was able to successfully select and execute its behaviors in the corresponding activity states using the learned policy.

### B. Discussions

Overall, our system architecture was able to accurately learn and implement Bingo games with a group of players. The time taken for non-experts to demonstrate a complete bingo game using our architecture is much faster than the time it takes to play an individual game. Namely, a game took on average 30 minutes in our experiments, this is comparable to the length of time it would take to physically demonstrate a complete game to Tangy with a group of players. It took three Bingo game demonstrations for the policy to be learned, this was due to the fact that not every help scenario was represented in every game in the simulator, as the game scenarios were randomly generated. We verified that if all scenarios were present in a single Bingo game demonstration, then the activity policy was able to be effectively learned in one demonstration.

In our experiments, the players always followed Tangy’s instructions during the Bingo games. However, this may not be the case with our intended population, as older adults living in long-term care facilities may not act deterministically due to cognitive impairments that could negatively impact their memory, ability to focus, and ability to make decisions [5]. Prior to implementation in these settings, it may be beneficial to have input from the care staff regarding the behaviors of the robot. For example, having care staff adding alternative behaviors for activity states to promote person-centered care [29]. For our future work, we intend to investigate the use of LfD methods in order to have care staff demonstrate primitive robot behaviors that can be

TABLE I. EXECUTED ROBOT BEHAVIORS DURING IMPLEMENTATION

Actual Activity State	Actual Assistance Request State	Actual User Activity State	Actual Robot Behavior	Success Rate	Total Instances of Activity State
Start	ANR	Occluded	Greeting	100%	20
Socialize	ANR	Occluded	Joke	100%	28
Facilitate	ANR	Occluded	Call Bingo number	100%	666
Help	AR	Bingo	Celebrate	100%	20
Help	AR	Incorrectly Marked	Request to remove markers from numbers that have not been called	100%	28
Help	AR	Missing Numbers	Request to mark numbers that have been called	100%	19
Help	AR	Correctly Marked	Encourage user to keep up the good work	100%	20
Help	AR	Occluded	Request to move card closer to robot	100%	7
Navigate	AR	Occluded	Navigate to user	100%	39
Navigate	ANR	Occluded	Navigate to front of room	100%	39
End	AR	Occluded	Valediction	100%	20

\*ANR = Assistance not required, AR = Assistance Required

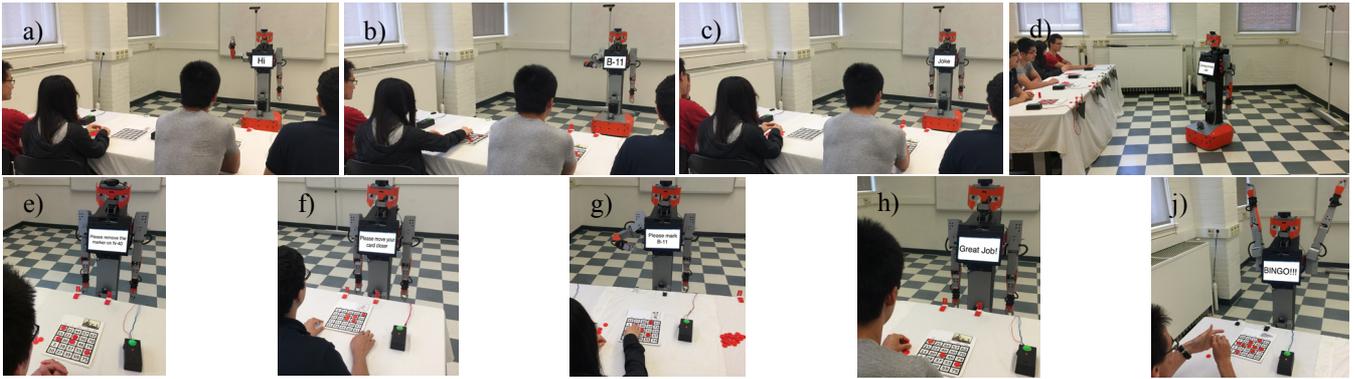


Figure 5. Robot Behaviors: a) Greeting; b) Call Number; c) Joke; d) Navigate to user; e) Request to remove markers from numbers that have not been called; f) Request to move card closer to robot; g) Request to mark numbers that have been called; h) Encourage user to keep up the good work; and i) Celebrate.

effective in obtaining compliance during such cognitively stimulating activities, in order to promote engagement and interaction. We will also investigate learning methods for dealing with uncertainties during the facilitation of a learned group activity in real-world settings.

## VII. CONCLUSIONS

In this paper we propose a demonstration learning system architecture for a social robot to learn new group activities from non-experts. Namely, the system architecture allows non-experts to demonstrate group activities through a simulator that models a social robot, a group of users, and the activity. From these demonstrations, the architecture can then learn a policy to facilitate a new group activity. System performance experiments show that the system architecture efficiently and accurately learned the policy for facilitating the group activity of Bingo from demonstrations by non-experts. The policy was also successfully implemented on a social robot to autonomously facilitate the group activity Bingo with multiple players.

## ACKNOWLEDGMENT

The authors would like to thank Sharaf Mohamed and Dami Choi for their assistance with this research.

## REFERENCES

- [1] United Nations, "World Population Ageing 2013," United Nations, Department of Economic and Social Affairs, Population Division, Rep. ST/ESA/SER.A/348, 2013.
- [2] A. Milan & N. Bohnert, "Living arrangements of seniors," Statistics Canada, Ottawa, Rep. #98-312-X2011003, 2011.
- [3] S. Sharkey, "People Caring for People: Impacting the Quality of Life and Care of Residents of Long-Term Care Homes," Ontario Ministry of Health and Long-term Care, Toronto, ON, 2008.
- [4] Ontario Council of Hospital Unions/CUPE, "Long-term Care in Ontario: Fostering Systemic Neglect," Focus Group Study Report, available at: <http://www.ochu.on.ca> (accessed July 2015), 2014.
- [5] M. C. Janke, L. L. Payne, & M. V. Puybroeck, "The role of informal and formal leisure activities in the disablement process," *Int J. of Aging and Human Development*, Vol. 67, No. 3, pp. 231-257, 2008.
- [6] W. G. Louie et al., "An autonomous assistive robot for planning, scheduling and facilitating multi-user activities," *IEEE Int. Conf. in Robotics and Automation*, pp. 5292-5298, 2014.
- [7] R. Khosla et al., "Embodying care in Matilda: an affective communication robot for the elderly in Australia," *ACM SIGHIT Proc. of Int. Health Informatics Sym.*, pp. 295-304, 2012.
- [8] M. Kanoh et al., "Examination of practicability of communication robot-assisted activity program for elderly people," *J. of Robotics and Mechatronics*, Vol. 23, No. 1, pp. 3-12, 2011.
- [9] T. Hamada et al., "Robot therapy as for recreation for elderly people with dementia-Game recreation using a pet-type robot," *IEEE Int. Sym. on Robot and Human Interactive Comm.*, pp. 174-179, 2008.
- [10] W. G. Louie et al., "Socially Assistive Robots for Seniors Living in Residential Care Homes: User Requirements and Impressions," *Human-Robot Interactions: Principles, Technologies and Challenges*, D. Coleman, New York: Nova Science Publishers, 2015, pp. 75-108.
- [11] B. D. Argall et al., "A survey of robot learning from demonstration," *Robotics and Autonomous Systems*, Vol. 57, pp. 469-483, 2009.
- [12] A. Billard, K. Dautenhahn, & G. Hayes, "Experiments on human-robot communication with robota, an imitative learning and communicating robot," *Int. Conf. of the Society for Adaptive Behavior*, pp. 1-12, 1998.
- [13] B. Akgun et al., "Trajectories and keyframes for kinesthetic teaching: a human-robot interaction perspective," *IEEE Int. Conf. on Human-Robot Interaction*, pp. 391-398, 2012.
- [14] C. Chao, M. Cakmak, & A. Thomaz, "Towards grounding concepts for transfer in goal learning from demonstration," *IEEE Int. Conf. on Development and Learning*, Vol. 2, pp. 1-6, 2011.
- [15] M. Cakmak, C. Chao, & A. Thomaz, "Designing interactions for robot active learners," *IEEE Trans. on Autonomous Mental Development*, Vol. 2, No. 2, pp. 108-118, 2010.
- [16] A. Lockerd & C. Breazeal, "Tutelage and socially guided robot learning," *IEEE Int. Conf. on Intelligent Robots and Systems*, pp. 3475 - 3480, 2004.
- [17] I. Lutkebohle et al., "The curious robot - structuring interactive robot learning," *IEEE Int. Conf. on Robotics and Automation*, pp. 4156 - 4162, 2009.
- [18] D. H. Grollman & O. C. Jenkins, "Dogged learning for robots," *IEEE Int. Conf. on Robotics and Automation*, pp. 2483 - 2488, 2007.
- [19] ROS, "Navfn", Available: <http://wiki.ros.org/navfn> [Accessed 2015].
- [20] J. Aleotti et al., "Leveraging on a virtual environment for robot programming by demonstration," *Robotics and Autonomous Systems*, Vol. 47, No. 2, pp. 153-161, 2004.
- [21] Carnegie Mellon University, "CMU Sphinx", Available: <http://cmusphinx.sourceforge.net/> [Accessed 2015].
- [22] J. R. Quinlan, "Induction of decision trees," *Machine learning*, Vol. 1, No. 1, pp. 81-106, 1986.
- [23] B. P. Sobel, "Bingo vs. physical intervention in stimulating short-term cognition in Alzheimer's disease patients," *American J. of Alzheimer's Disease & other Dementias*, Vol.16. No.2, pp.115-120, 2001.
- [24] G. Grisetti, C. Stachniss, & W. Burgard, "Improved Techniques for Grid Mapping with Rao-Blackwellized Particle Filters," *IEEE Trans. on Robotics*, Vol. 23, pp. 34-46, 2007.
- [25] S. Thrun, W. Burgard, & D. Fox, "Mobile Robot Localization," *Probabilistic Robotics*, pp. 157-184, 2005.
- [26] Omron, "OKAO Vision", Available: [http://www.omron.com/r\\_d/coretech/vision/okao.html](http://www.omron.com/r_d/coretech/vision/okao.html) [Accessed 2015], 2007.
- [27] B. Herbert et al., "Speeded-Up Robust Features (SURF)", *Computer Vision and Image Understanding*, Vol. 110, No. 3, pp. 346-359, 2008.
- [28] R. Duda & P. Hart, "Use of the Hough Transformation to Detect Lines and Curves in Pictures", *Communications of the ACM*, Vol. 15, No. 1, pp. 11-15, 1972.
- [29] K. Grosch, L. Medvene, & H. Wolcott, "Person-Centered Caregiving Instruction for Geriatric Nursing Assistant Students," *J. of Gerontological Nursing*, Vol. 34, No. 8, pp. 23-31, 2008.