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Can I be of Assistance? The Intelligence behind an Assistive Robot

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Abstract— **The social interaction, guidance and support that a socially assistive robot can provide a person can be very beneficial to patient-centered care. However, there are a number of conundrums that must be addressed in designing such a robot. This work addresses two main limitations in the development of intelligent task-driven socially assistive robots: (i) recognition and identification of human gesticulation as a source of determining the affective state of a person, and (ii) robotic control architecture design and implementation with explicit social and assistive task functionalities. In this paper, the development of a unique task-driven robotic system capable of quantitatively interpreting human body language and in turn, effectively responding via task-driven behavior during assistive social interaction is presented. In particular, a novel gesture identification and classification technique is proposed capable of interpreting human gestures as semantically meaningful commands for inputs into a multi-layer decision making control architecture. The learning-based control architecture is then utilized to determine the effective and appropriate assistive behavior of the robot.**

I. Introduction

As the U.S. prepares for the first round of baby boomers to turn 65 in 2011, it must prepare for the approximate 8 million that could need long term care from nursing homes and home health providers by 2040 [1]. To meet these challenges, healthcare organizations need to adopt the use of advanced information technologies in their patient care process. In particular, the development of innovative social assistive robots can help minimize the threats of nursing shortages, and provide measurable improvements in an individual's health status [2].

Separate studies utilizing creature-like robots, Pearl, [3], and Paro, [4], in nursing homes have demonstrated the positive response of elders to these robots, suggesting the potential use of assistive robots as robotic aids. In addition to creature-like assistive robots, whose interaction functions are limited, non-contact *human-like* interactive assistive robots have also been developed. These robots mainly consist of a wheeled vehicle carrying a computer monitor projecting an image of a software agent or human [i.e., 5,6]. To date these robots are unable to engage in intelligent emotion-based bi-directional interactions. To address this limitation, this work focuses on the investigation of socially assistive robots, with *human-like demeanors,* and high level affect recognition and identification and decision making abilities, capable of natural and believable social interaction via verbal and non-verbal communication. In order to achieve this type of human-robot interaction (HRI), modeling of the relationship that connects human and robot intelligence is required. HRI robots can potentially have a high degree of autonomy, and cognitive and emotional capabilities. For naturalistic social interactions to take place, the investigation into the development of novel approaches for intelligent robots, capable of identifying, understanding and reacting to human intent and affective state is needed. Recent studies into human-robot interaction have concluded that the need for social intelligence in HRI robots is extremely important in a healthcare/eldercare environment [7].

This paper addresses two main limitations in the development of intelligent task-driven non-contact social assistive robots: (i) recognition and identification of human gesticulation as a source of determining the affective state and intent of a person, and (ii) control architecture design and implementation with explicit social and assistive task functionalities. In this paper, the development of a unique task-driven robotic system capable of quantitatively interpreting human body language and in turn, effectively responding via task-driven behavior during assistive social interaction is presented. In particular, a novel gesture identification and classification technique proposed by the authors capable of interpreting human gestures as semantically meaningful commands is used to provide inputs into a multi-layer decision making control architecture. The learning-based control architecture is then utilized to determine the effective and appropriate behavior of the robot. The overall proposed system is shown in Fig. 1.

II. Gesture Identification and Recognition

An important design issue that must be addressed for socially assistive robots is the robot's ability to judge the affective state of humans in order to respond accordingly during interaction. Non-verbal communication has been deemed to be more meaningful than verbal content, especially in demonstrating changes in mood/emotional state [8]. The use of non-verbal communication for detecting human emotional states normally involves the use of vision based gesture recognition systems [9-12].

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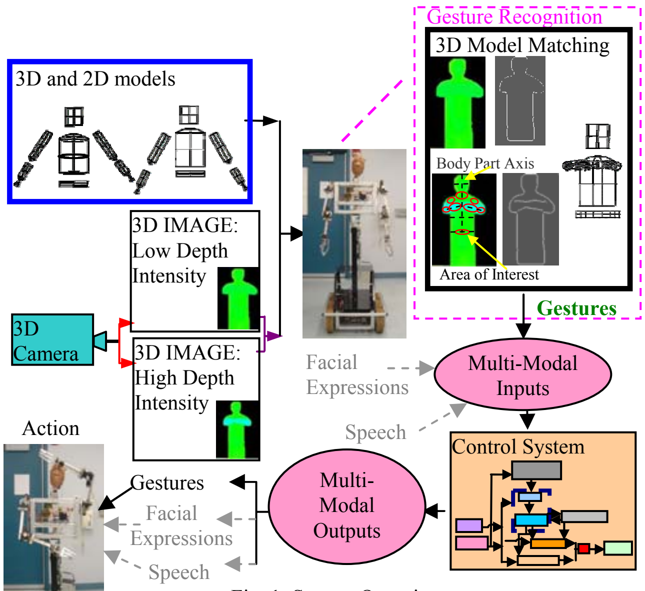

Fig. 1: System Overview

In order to address the limitations of current gesture sensing and recognition techniques, we propose the development of a unique 3D model based technique that can recognize human upper body gestures via *varying intensity* 3D images, provided by a 3D camera. The proposed system can be utilized as an input modal into a multi-modal human-robot interaction scheme along with other nonverbal (i.e., facial expressions) or verbal (i.e., speech recognition) modals for effective recognition of a human's emotional state during interaction.

The main advantages of the proposed method are that it can directly provide 3D pose information: (i) without the use of multiple cameras, (ii) in a non-contact manner without restricting the human, and (iii) in real-time to assist in minimizing computational complexity.

A quantitative model representation of body part motion parameters is developed to recognize the movements depicted in the 3D images as appropriate gestures.

The motion of each body part can be represented by a combination of translational and rotational movements used to determine gestures that the human makes during interaction.

A. Model Matching

A multi-stage procedure is utilized in this work for determining the appropriate model transformation that corresponds to varying depth intensity images taken of a human during interaction. This gesture recognition approach consists of utilizing a low depth intensity image of the human and a high depth intensity image, Fig. 1. Both these types of images along with 3D depth information are utilized by a 3D model matching algorithm to identify the human silhouette and the pose of varying body parts. For a detailed explanation of the 3D model matching algorithm identifying the body part motion of the human, during interaction with the robot, the reader is referred to [13].

B. The Defined Gestures

The gestures to be identified by the proposed recognition technique are derived and modified according to the Davis Nonverbal States Scale (DNSS) [14]. DNNS is a coding method designed to analyze the positions, gesticulations and specific actions displayed by human participants in a one-on-one conversation. This work presents the *first application* of the DNNS to HRI environments. The advantage of the DNSS is its ability to directly correlate a person's gestures to his/her reaction to an encounter [14]. The gestures are defined according to: (i) trunk lean and orientation; and (ii) arm symmetry, location and orientation. Each of these body poses has a range of movement that allow the robot to determine the particular gesture of the human it is interacting with. For example, trunk orientation is defined as: Towards-where the person is oriented facing the robot, Neutral-where the trunk is facing slightly away from the robot by 3^o to 15^o and Away-where the trunk is oriented more than 15^o from the robot. There can be a great variety of possibilities for the gestures, i.e., further arm arrangements and hand placements, however, the scale can be justified by the fact that most people display a limited range of positions during interaction and will repeat these gestures during the course of the interaction [14].

III. HRI CONTROL ARCHITECTURE

In the literature a great deal of focus has been placed on low-level control architectures for robots to mimic human emotional expressions [15-17], and high-level multi-module control strategies utilized to generate emotions from the evaluation of the wellbeing of the robot during interaction [18-21]. In this paper, the design of a high-level multi-layer control architecture that shifts the emphasis from the wellbeing of the robot to the human is presented. In particular, the behavior of the robot will be determined based on the assistive task the robot must complete, where the robot's emotions are utilized to aid task completion. Thus, the robot is said to be task-driven as opposed to the emotion-driven HRI robots in the literature. Emotions are utilized as a secondary consideration to assist the robot in accomplishing its tasks.

The proposed control architecture is adapted from the Cognition and Affect (Cogaff) information processing architecture [22] and the emotional control system (ECS) [23]. The combined approach consists of modules from the two architectures that are best suited for assistive robotic applications and will view emotions as parameters of an intelligent system used in the decision making process, Fig. 2. In particular, the reactive and deliberative layers from the CogAff architecture are utilized, in which the reactive layer is used mainly for interaction situations that require an immediate response, whereas the deliberative layer contains decision making capabilities that analyze scenarios. The ECS architecture, using a drives module and an emotional supervisory system, is adapted herein to assist in behavior selection.

Herein, robot behaviors are considered either emotional or non emotional, based on the situation the robot is in. The robot control architecture proposed in this work can be explained as follows. The inputs to the control system include the affective state of the person interacting with the robot (as defined herein by gestures) and the robot's internal/external sensory information. The robot's tasks are stored in the long term memory module, Fig. 2. Once the robot identifies the person it is interacting with, tasks specific to that person will be sent to the drives module. Since the focus of this research work is on non-contact socially assistive robots, the defined tasks that the robot will accomplish during interaction may include monitoring, and providing companionship and reminders to patients. The drives module will also consist of drives directly related to the robot's health (i.e., power, operation of motors) as updated from the robot's sensors. Dominant drives will then be utilized to assist in determining the robot's emotional state via the emotional state system, and the output behavior via the reactive or deliberative layer. The emotional state is stored in the short term memory. The priority module decides the final behavior of the robot based on the precedence of information regarding robot and human health and safety during interaction.

There are two main reasons why the current emotional state of the robot should be known during the decision making process: (i) the task to be completed does not match the current emotion of the robot, i.e., the robot needs to provide companionship, the robot should not do so in a distress or angry manner, (ii) the emotional state of the robot is failing to complete the required task, i.e., the robot needs to monitor a resident in a nursing home, if a resident refuses to answer the robot's inquires, the robot must change its emotion accordingly in order to complete its task.

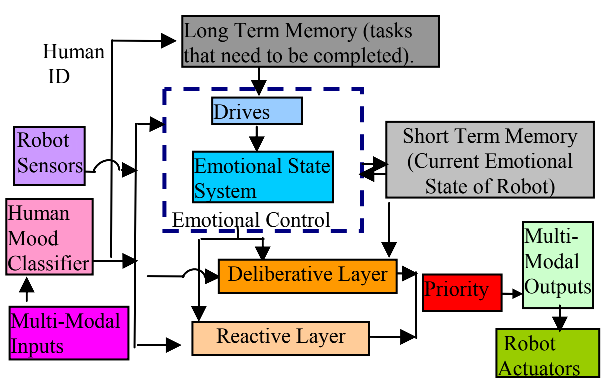

Fig. 2: Proposed Control Architecture.

Although there have been a number of emotional behavior architectures proposed in the literature [i.e., 20-25], few have been the subject of extensive implementation and analysis. The type of processing mechanisms to be utilized in each layer of the control architecture is usually left as the responsibility of the designer of the agent/robot. In this work, we investigate and evaluate the utilization of processing mechanisms in the context of task-driven socially assistive robots for our proposed architecture. The overall proposed architecture will be integrated and tested on Brian, the expressive *human-like* socially assistive robot capable of HRI, developed by Nejat et al. [13], Fig. 1.

An assistive robot's behavior should reflect the task it needs to complete and its emotional state should still result in the robot completing the task, unless the robot is physically incapable (e.g, not enough battery power). Hence, the objective is not to have the robot mimic human emotions, but to use emotions to assist in determining the behavior necessary for the robot to accomplish its tasks. The next two sections present the preliminary design of the human mood classifier and deliberative layer modules.

A. Human Mood Classifier: Gesture Classification

Within the Human Mood Classifier, the Nonverbal Interaction and States Analysis (NISA) of the DNSS is utilized to code the recognized gestures into a person's accessibility level [14]. In this work, we will utilize the human's accessibility level to reflect a human's affective state. NISA has shown that a significant relationship between gesticulation patterns and a person's accessibility can be determined. In particular, the Position Accessibility Scale of NISA will be utilized. The scale consists of 4 levels of accessibility ranging from Level 1 (least accessible) to Level IV (most accessible), which are categorized by the body trunk patterns such as towards (T), neutral (N) or away (A) from the robot and further divided into 3 sub-levels based on additional T,N or A arm patterns. Accessibility values will be utilized by the deliberative layer in order to assist in appropriately determining the robot's pro-active behavior. Our future work consists of correlating the human gestures detected by the robot with speech and facial expression detection methods for human mood classification based on multi-modal recognition.

B. Deliberative Layer

In interactive situations, it is difficult to model and predict, a priori, the potential events that will occur between humans and robots. Hence, in such situations it is important that the robot be able to learn from its own experiences during interaction. Within the proposed architecture, the deliberative layer will act as the main decision making module to allow for task-driven behavior. Our work focuses on the utilization and integration of reinforcement learning (RL) for robot intelligence. *RL has been tested in many simulated environments and real-world scenarios* [i.e., 26-28], but has yet to be applied and adapted to the field of socially *assistive* robots. RL has a number of advantages when compared to other robot learning and control techniques: (i) a priori information about the environment is not needed, and (ii) the learning process is on-line. In particular, in this work, we investigate the utilization of *Q*-learning.

In *Q*-learning a mapping is learned from a state-action pair to a value called *Q*. The mapping represents the reward of performing an action in a state. A controller then measures the state, chooses the action with the highest *Q* value and executes it [29]. The advantage of this approach is that it is model-less and can be exploration insensitive (Q values will converge to optimal values, independent of robot behavior during data collection) [29].

In particular, since human actions can be unpredictable when interacting with the robot, a nondeterministic Q-learning scheme is investigated, where rewards are represented by probability distributions. In this work, a non-deterministic Q-learning decision making scheme is proposed specific for task-driven socially assistive robots, as presented in Fig. 3. The robot starts in the current state: $s_0(y_{Hi}, y_{Ri}, d_i)$, and will perform an action (which results in the maximum Q value) that will lead it to satisfy its dominant drive, d_i. y_{Hi} represents the accessibility level of the human as defined by the DNNS and y_{Ri} is defined, herein, as the emotional state of the robot. Due to the uncertainty of the interaction, the drive may or may not be satisfied. If Action 1 is implemented and the drive is satisfied, the robot will reach state s_1, ready to perform a new set of tasks that will be updated with new emotion and drive information (i.e., y_{Hi+1}, y_{Ri+1}, d_{i+1}). If the drive is unsatisfied, the robot will move into state s_2, where it will attempt to continue to satisfy its current drive, by updating its emotional state and the accessibility level of the human. For our nondeterministic environment, Q can be determined by [30]:

$$Q(s,a) = r(s,a) + \gamma \textstyle\sum_{s'} P(s'|s,a) \max_{a'} Q(s',a'), \qquad (2)$$

where r is the immediate reward function, γ is the discount factor and is set between 0 and 1 (γ expresses preference for future awards, i.e., a higher value places more emphasis on future awards), s' is the state resulting from applying action a to state s, and a' are the actions applicable to the new state. $P(s'|s,a)$ is the probability of the resultant state based on the performed action. Experiments used to verify the proposed layer are presented in the next section.

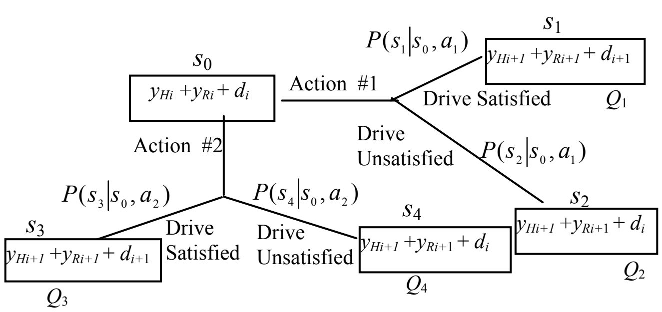

Fig. 3: Learning-Based Deliberative Layer

In order to implement the proposed methodology, the emotional states, drives and actions of the socially assistive robot must be defined. Ekman identified happiness, sadness, fear, anger, disgust and surprise as 6 basic universal emotions among humans [31]. Herein, we will explore the utilization of these emotions as the emotional states of the robot.

C. A Proof-of-Concept Example

A simple numerical example is presented to illustrate the aforementioned methodology. Mr. Smith is 72 years old and has a history of heart attacks and strokes in his family. He, himself, has high blood pressure. It is imperative that he takes one beta blocker everyday. The scenario for the assistive robot is as follows:

Current Drive, d_i: to get Mr. Smith to take his medication
Dominant Robot Emotion, y_{Ri}: happy
Human Accessibility Level y_{Hi}: Level III.
Action #1: Robot speaks in a loud stern, yet pleasant voice with arms crossed, "Mr. Smith, it is time for you to take your medication."
Action #2: Smiling continuously with pauses between words in an upbeat voice, the robot instructs Mr. Smith to take his medication: "Mr. Smith, you must take your medication now!"

One of two outcomes may result from each action: Mr. Smith will take his medication (Drive Satisfied) or Mr. Smith will not take his medication (Drive Not satisfied). A probability is assigned to each of these outcomes. For this particular example, the probabilities illustrated were determined based on survey results from 20 participants: $P(s_1|s_0,a_1) = 0.60$, $P(s_2|s_0,a_1) = 0.40$, $P(s_3|s_0,a_2) = 0.70$ and $P(s_4|s_0,a_2) = 0.30$. The Q max values for the states are defined as: *Max* Q_1=85, *Max* Q_2=71, *Max* Q_3=80 and *Max* Q_4=54. The reward function, r, for the different states is represented in the following tabular form:

State	S_0	S_1	S_2	S_3	S_4
	0	100	0	100	0

The value of the discount factor, γ, is set to 0.8.

The following steps are taken to determine the robot's behavior:

Step 1: Receive the initial state information of the robot, s_0.
Step 2: The robot chooses an Action based on the calculation of Equation (2). Herein, the Q values for Action #1 and Action #2 are determined to be 64 and 58, respectively. Therefore, Action #1 is considered to be the more desirable action for the robot to take.

IV. Experiments

Our preliminary experiments consist of the robot, Brian, and a human interacting in a one-on-one conversation standing approximately 1.5 m apart. Brian consists of a human-like demeanor having similar functionalities to a human from the waist up, Fig. 1. The robot is able to communicate via: (i) a unique human-like face, (ii) a 3 degrees-of-freedom (DOF) neck capable of expressing head gestures, and (iii) an upper torso consisting of a 2 DOF waist and two 4 DOF arms designed to mimic human-like body language. The robot is also able to communicate verbally using commercial interactive conversation software. In addition to the 3D camera, the robot uses a 2D digital camera and a laser scanner to track a person and to ensure that the optimal distance required for effective gesture identification is maintained. Human subjects participating in the experiments ranged in age from 16 to 30 years old. In the experiments, the human was asked to implement a number of predefined gestures for perception, identification and categorization in the appropriate accessibility levels. Experiments were conducted to evaluate the potential use of the proposed gesture identification and categorization methodology and *Q*-learning algorithm in a HRI environment.

A. Gesture Categorization

Low and high intensity 3D images of the human were taken and analyzed. Fig. 4 presents four different gestures of a person in a: (i) neutral position where the body is upright and the arms are to the sides, (ii) neutral position with arms folded, (iii) neutral position with one arm propped up by the other arm, and (iv) leaning forward with head slightly down and arms at the sides. By utilizing the previously developed model matching recognition technique the location of the occluded and non-occluded body parts were determined to approximate the appropriate 3D model. Body part orientations were deduced from depth images by correlating depth values with rotation angles. For example, when detecting upper trunk orientation, the upper trunk *away* position is defined to be when the trunk is oriented at more than 15^o from the robot. It would be computationally expensive to detect the exact orientation angles, however, by directly sampling the depth information from the high intensity depth image, a significant change in depth on either side of the rotational joint is observed. A less subtle change would exist if the orientation was approximately between 3^o to 15^o (*neutral* orientation) and approximately no change would be detected in the *toward* orientation (0^o to 3^o). For the lean forward position, the depth information indicates that the upper portion of the head has smaller depth values than the lower part of the head and chest.

Once the appropriate 3D model is approximated, and the corresponding gestures determined, the person's level of accessibility is determined based on trunk and arm locations and orientations. The level of accessibility (i.e., y_{Hi}) for the four poses present in Fig. 4 utilizing NISA are determined to be: Level IV for Fig. 4(a),(c) and (d), and Level III for (b). This information is used to determine the necessary states for the *Q*-learning algorithm.

B. Q-learning

The assistive drives for these experiments were chosen to mimic a real-world assistive environment. The robot's drives were chosen so that the robot would provide the following daily activity reminders to the person: when to eat, use the bathroom, go for a walk and take necessary medication.

The robot emotions of happiness, sadness, fear, and anger were utilized. These emotions were determined based on a priority look-up table. 48 different states were created based on all possible combinations of y_{Hi}, y_{Ri} and d_i. A database of five potential robot behavior actions for each state was also created.

In this experiment, 5 participants were used to determine the initial probability values and *Q* values for the respective action-state pairs. 10 separate participants were then used to test the feasibility of the algorithm in the proposed assistive manner. In order to assess if the drive had been satisfied, each person was asked to verbally state "yes" after the robot's action was implemented, at which time the robot would move to the next task. If the drive was not satisfied, the person would say "no" and the robot would continue to try to satisfy the drive. Fig. 5 shows the average number of iterations needed to satisfy the robot's respective drives. In general, it took 1 or 2 iterations to satisfy the drives. The exception is the drive related to using the bathroom, which took 5 iterations. We postulate that this result is due to the fact that people may be uncomfortable and resistive to orders from others to go to the bathroom.

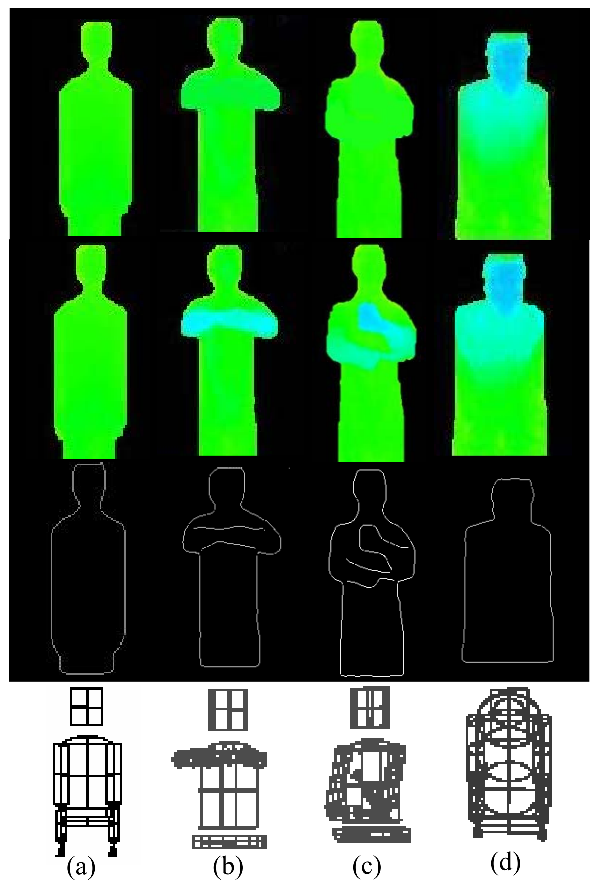

Fig. 4: (a) Neutral Position, (b) Neutral Position with Arms Crossed, (c) Neutral Position with One Arm Propping Another, and (d) Lean Forward Position [3D models of (b) and (c) are slightly turned clockwise to show the details of the gestures].

V. CONCLUSIONS

The proposed work focuses on the following areas of research in natural HRI environments for non-contact socially assistive robots: (a) body gesture recognition and categorization, and (b) robotic HRI control architecture. The aim is to advance technologies related to natural HRI environments in order to promote bi-directional communication: In particular, the development of robotic systems capable of quantitatively interpreting human body language and in turn, effectively responding via task-driven behavior during assistive social interaction. Preliminary experiments show the potential of integrating the proposed methodologies into robotic systems to perform interactions with people. Our future work consists of correlating the human gestures detected by the robot with speech and facial expression detection methods for multi-modal recognition and, furthermore, extending the proposed recognition technique to cluttered environments. In addition, the controller will be expanded to address the remaining modules presented in the architectural design. Experiments in real world settings with larger participants will also be conducted.

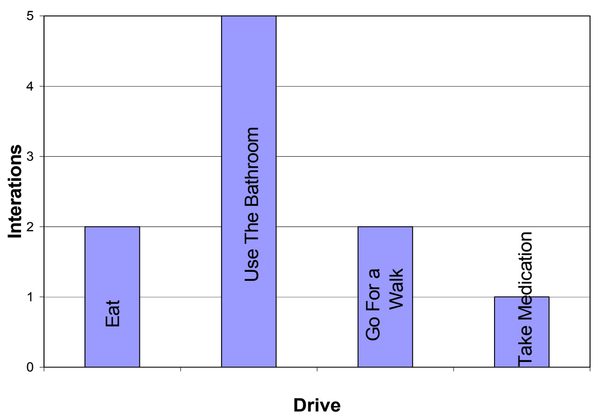

Fig. 5: *Q*-learning Results.

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REFERENCES

[1] S. R. Kunkel and R. A. Applebaum, "Long-term Care For The Boomers: A Public Policy Challenge for the Twenty-first Century," Prepared for the Office of the Assistant Secretary for Planning and Evaluation, U.S. Department of Health and Human Services, pp. 1-18, 1991.

[2] M. Nies, G. Nejat, Y. Sun, and T. Sexton, "A Multidisciplinary Team Program of Research with Interactive Nurse Robots to Enhance Elderly Health," Sigma Theta Tau Int. Nursing Research Congress Focusing on Evidence-Based Practice, Vienna, Austria, 2007.

[3] M. Montemerlo, J. Pineau, N. Roy, S. Thrun, and V. Verma, "Experiences with a mobile robotic guide for the elderly," National Conference on Artificial Intelligence, Edmonton, Canada, Vol. 18. pp 587-592, 2002.

[4] K. Wada, T. Shibata, T. Saito and K. Tanie, "Robot Assisted Activity for Elderly People and Nurses at a Day Service Center, IEEE Int. Conference on Robotics &Automation, Washington, DC, pp. 1416-1421, 2002.

[5] K. Sato, M. Ishii, and H. Madokoro, "Testing and evaluation of a patrol robot system for hospitals," Electronics and Communications in Japan (Part III: Fund. Elect. Sci.), Vol. 86, No. 12, pp. 14- 26, 2003.

[6] K.I. Kang, S. Freedman, M.J. Mataric, M.J. Cunningham, and B. Lopez, "A hands-off physical therapy assistance robot for cardiac patients," IEEE Int. Conf. on Rehabilitation Robotics, Chicago, IL, pp. 337-340, 2005.

[7] M. Heerink, B. Kröse, B. Wielinga, and V. Evers, "Human-Robot User Studies in Eldercare: Lessons Learned," Assistive Technology Research Series, Vol. 19, 2006.

[8] D. Morris, P. Collett, P. Marsh, and M. O'Shaughnessy, Gestures, their Origin and Distribution, London: Jonathan Cape Ltd, 1979.

[9] M. Hasanuzzaman, T. Zhang, V. Ampornaramveth, H. Ueno, "Gesture-based Human-Robot Interaction Using a Knowledge-based Software Platform." Industrial Robot, Vol. 33, No. 1, pp. 37-49, 2006.

[10] H. Park et al., "HMM-Based Gesture Recognition for Robot Control," Pattern Recognition and Image Analysis, Vol. 3522, pp. 607-614, 2005.

[11] V. Bonato et al., "A Real Time Gesture Recognition System for Mobile Robots," Int. Conf. on Informatics in Control, Automation and Robotics, Setúbal, Portugal, pp. 207-214, 2004.

[12] S. Knoop, S. Vacek, and R. Dillmann, "Sensor Fusion for 3D Human Body Tracking with an Articulated 3D Body Model," IEEE Int. Conf. on Robotics and Automation, Orlando, Florida, pp. 1686-1691, 2006.

[13] G. Nejat, B. Allison, N. Gomez, and A. Rosenfeld, "The Design of an Interactive Socially Assistive Robot for Patient Care," ASME Int. Mechanical Engineering Congress and Expo, Seattle, WA, IMECE2007-41811, 2007.

[14] M. Davis, and D. Hadiks, "Nonverbal Behavior and Client State Changes during Psychotherapy," Journal of Clinical Psychology, Vol. 46, No. 3, pp. 340-35, 1990.

[15] T. Hashimoto, M. Senda, and H. Kobayashi, "Realization of realistic and rich facial expressions by face robot," IEEE Tech. Exhibition Based Conference on Robotics and Automation, Tokyo, Japan, pp. 37-38, 2004.

[16] K. Hayashi, Y. Onishi, K. Itoh, H. Miwa, and A. Takanishi, "Development and evaluation of face robot to express various face shape," IEEE Int. Conf. on Robotics and Automation, Orlando, Fl., pp. 481-486, 2006.

[17] W. Weiguo, and M. Qingmei, "Development of the humanoid head portrait robot system with flexible face and expression," IEEE Int. Conf. on Robotics and Biomimetics, Shenyang, China, pp. 718-723, 2004.

[18] C. Breazeal and B. Scassellati, "A context-dependent attention system for a social robot," Int. Joint Conf. on Artificial Intelligence, Stockholm, Sweden, pp. 1146-1151, 1999.

[19] S. Thrun et al., "MINERVA: A Second-Generation Museum Tour-Guide Robot," IEEE Int. Conf. on Robotics and Automation, Detroit, MI, pp. 1999-2005, 1999.

[20] H.-R. Kim, K.W. Lee, and D.S. Kwon, "Emotional Interaction Model for a Service Robot," IEEE Int. Workshop on Robots and Human Interactive Communication, Nashville, TN, pp. 672-678, 2005.

[21] J.D. Velasquez, "Modeling Emotions and Other Motivations in Synthetic Agents," National Conf. on Artificial Intelligence (AAAI-97), Providence, RI, pp. 10–15, 1997.

[22] A. Sloman, "Varieties of affect and the CogAff architecture schema," AISB'01 Symp. on Emotion, Cognition, and Affective Computing, York, England, pp. 39-48, 2001.

[23] M. Malfaz and M. A. Salichs, "A new architecture for autonomous robots based on emotions," IFAC Symp. on Intelligent Autonomous Vehicles, Lisbon, Portugal, 2004.

[24] N. Frijda, The Emotions, Cambridge: Cambridge University Press, 1986.

[25] A. Ortony, G. Clore, and A. Collins, The Cognitive Structure of Emotions, Cambridge: Cambridge University Press, 1988.

[26] W.D. Smart, and L.P. Kaelbling, "Effective reinforcement learning for mobile robots," IEEE Int. Conf. on Robotics and Automation, Washington, DC, pp. 3404-3420, 2002.

[27] T. Martínez-Marín, and T. Duckett, "Fast Reinforcement Learning for Vision guided Mobile Robots," IEEE Int. Conf. on Robotics and Automation, Barcelona, Spain, pp. 1425-1430, 2005.

[28] M.J. Mataric, "Reinforcement Learning in the Multi-Robot Domain," Autonomous Robots, Vol. 4, No. 1, pp. 73-83, 1997.

[29] C. Gaskett, D. Wettergreen and A. Zelinsky, "Reinforcement Learning applied to the control of an Autonomous Underwater Vehicle," Australian Conf. on Robotics and Automation, Brisbane, Australia, pp. 121-135, 1999.

[30] T. Mitchell, Machine Learning, Boston: McGraw-Hill, 1997.

[31] P. Ekman, "An argument for basic emotions," Cognition and Emotion, Vol. 6, pp. 169-200, 1992.