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AN INTELLIGENT SOCIALLY ASSISTIVE ROBOT FOR HEALTH CARE

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ABSTRACT

The development of socially assistive robots for health care applications can provide measurable improvements in patient safety, quality of care, and operational efficiencies by playing an increasingly important role in patient care in the fast pace of crowded clinics, hospitals and nursing/veterans homes. However, there are a number of research issues that need to be addressed in order to design such robots. In this paper, we address two main limitations to the development of intelligent socially assistive robots: (i) identification of human body language via a non-contact sensory system and categorization of these gestures for determining the accessibility level of a person during human-robot interaction, and (ii) decision making control architecture design for determining the learning-based task-driven behavior of the robot during assistive interaction. Preliminary experiments presented show the potential of the integration of the aforementioned techniques into the overall design of such robots intended for assistive scenarios.

1. INTRODUCTION

As baby boomers approach retirement age, most countries are unprepared to meet the social and economic needs of this increasing elderly population. For example, 20-32% of the population of Italy, Germany, Japan and the U.S. will be elderly in the next few decades [1,2]. Billions of dollars will need to be invested to accommodate and care for this population in hospitals, nursing, veterans and private homes. In addition, what makes this reality even more difficult to address is that according to the World Health Organization, health care professionals such as nurses, pharmacists, doctors, therapists and other related professions are experiencing a significant shortage in their work force [3].

To meet these challenges, healthcare organizations need to implement the use of advanced technologies in their patient care process. In particular, the development of innovative assistive robots can help reduce the threat of health care professional shortages, and provide improvements in patient safety, quality of care and operational efficiencies.

Assistive robotics is a growing research area. Assistive robots can be classified into two types: (i) contact or (ii) non-contact. The former group of robots includes surgical and active assistant physical therapy robots, for which the robots make physical contact with the respective patient. The non-contact group of assistive robots consists of robots that are designed to have minimal or no physical contact with the patient. This group includes robots that are utilized to deliver medication to patients, medical records to nurses, surgical tools to doctors and help the patient with non-physical contact therapy, i.e., accompany patient on daily walking exercises, or repetitive muscle exercises.

In recent years a handful of attempts have been made to develop socially assistive robots for human care in hospitals, medical and rehabilitation centers and as assistants for physical therapy. For example, Paro is a toy-like interactive robot modeled after a baby seal, having fur, whiskers, moving eyes and flippers. Paro responds to touch, sound, sight, and temperature [4]. Studies directly involving Paro have shown that introducing the seal-like robot to the elderly has the potential of improving their moods, reducing their dependency on the nursing staff and decreasing Burnout scores for the nursing staff. Similarly, Kaspar (Kinesics and Synchronization in Personal Assistant Robotics) is a child sized humanoid robot designed to encourage basic social interaction skills in children with Autism using turn-taking and imitation games [5]. Pearl is a socially assistive robot that was designed to be used to remind elderly people about their daily activities [6]. Pearl has a cartoon-like face with moving eyes and eyebrows that allow her to express emotions and a touch screen monitor for communication. Other robots include CLARA [7], Patrol robot [8] and SIRA [9], each of which consist of a wheeled vehicle carrying a computer monitor projecting an image of a software agent or human. Typically, the majority of these robots have been 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.

The social interaction, guidance and support that a socially assistive robot capable of bi-directional interaction can provide a person can be very beneficial in elderly care. However, there are a number of difficulties that must be addressed in designing such socially assistive robots. In particular, two main limitations include: (i) recognition and identification of human gesticulation as a source of determining the affective state of a person, and (ii) the robotic control architecture design and implementation with explicit social and assistive task functionalities. Our work consists of the development of a unique intelligent task-driven non-contact socially assistive robot consisting of a human-like demeanor for utilization in hospital wards, nursing and veteran homes and to study its role and impact on the quality of elderly care. The robot is an embodied entity that will participate in hands-off non-contact social interaction with a person during the convalescence, rehabilitation or end-of-life care stage. In particular, the robot is capable of quantitatively interpreting human body language and in turn, effectively responding via task-driven behavior during assistive social interaction. In this paper, the design of a novel gesture recognition, identification and classification technique capable of tracking and interpreting human gestures as semantically meaningful commands for input into a unique multi-layer decision making control architecture is proposed. Depth and thermal images from a 3D camera and a thermal camera are used for visual perception and characterization of gestures. The learning-based control architecture is utilized to determine the effective and appropriate behavior of the assistive robot. Preliminary experiments show the potential of the proposed intelligent robotic system for autonomous interactions with people.

The rest of the paper is organized as follows. Section 2 describes the proposed gesture recognition and identification system. In Section 3, the control architecture is introduced. Experimental results are presented in Section 4. Lastly, concluding remarks are presented in Section 5.

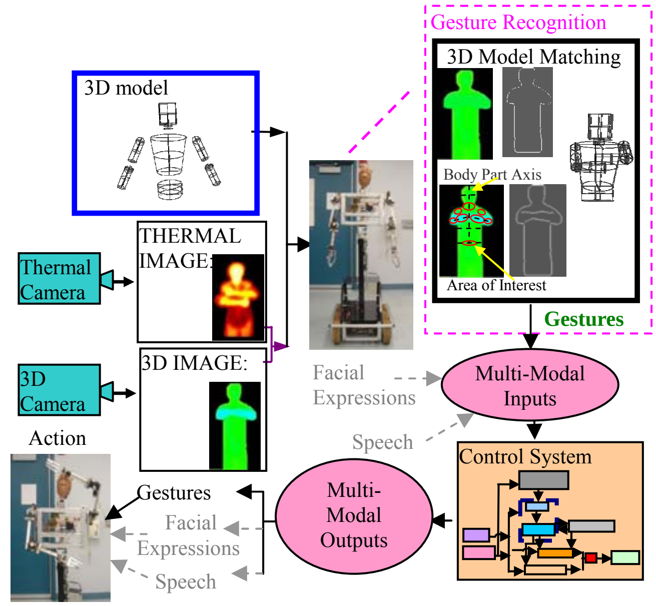


Fig. 1: System Overview.

2. GESTURE IDENTIFICATION AND RECOGNITION

In this section the robot's ability to identify and judge the affective state of the human it is interacting with is analyzed. In particular, a gesture identification scheme is proposed that uses nonverbal communication techniques for gesture recognition. Non-verbal communication has been deemed to be more meaningful than verbal content, especially in demonstrating changes in mood/emotional state [10]. The use of non verbal communication for detecting human emotional states typically involves the use of vision based gesture recognition systems [11,12]. In this work, we present the first application of a sensory system consisting of a 3D camera and a thermal camera for 3D gesture recognition and characterization, Fig 1. The main advantages of this sensory system over current methods are that it can directly provide 3D pose information and human body thermal information: (i) in a non-contact manner without restricting the human, and (ii) in real-time to assist in minimizing computational complexity. Real-time 3D, 2D and thermal information will be utilized from our sensory system as inputs into our 3D model-based gesture recognition algorithms.

3D MODEL

The model developed is a volumetric 11 degrees-of-freedom (DOF) model consisting of simple geometric shapes (i.e., cubes, cones and cylinders) in order to minimize the number of model parameters, Fig. 2. The DOF for each body part are defined by the gestures that need to be recognized. Each of DOF has a lower and higher value limit that can be determined from static biomechanical constraints and gesture design constraints. Table 1 outlines the DOF for each body part.

The motion of each body part can be represented by a combination of translational, $\mathbf{t}_l$, and rotational, $\mathbf{R}_l$, movements, as defined in Table 1, to be utilized to determine appropriate gestures that the human makes during interaction. This motion can be represented with respect to the local frame of the body part $\mathbf{M}_{li}$ $(\mathbf{t}_l,\mathbf{R}_l)$ and, in general, to the global frame of the overall model as $\mathbf{M}_{mi}$ $(\mathbf{t}_m,\mathbf{R}_m)$, defined as the coordinate frame of the lower trunk.

Table 1: DOF for Body Parts.

Body Part	# DOF	Description of Motion
Head	3	3 rotational DOF for head tilt up and down, tilt left and right, and turn away.
Upper Trunk	3	3 rotational DOF for lean forward or back, tilt left or right, and turn away.
Lower Trunk	1	1 rotation DOF for turn away.
Upper Arm	3	1 rotation DOF for swing and 1 rotation DOF for lift up and down and 1 rotation for lift laterally.
Lower Arm	1	1 rotation DOF for turn towards or away (i.e., bow).

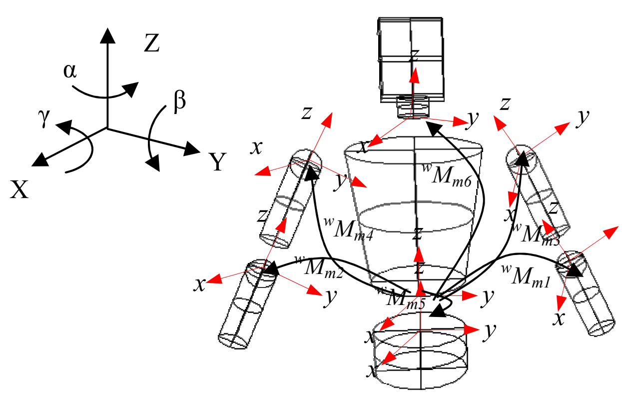


Fig 2: 3D Model.

3D MODEL MATCHING

The proposed 3D model-based gesture recognition technique is presented in the following five steps:

1. Initialization of Model:

At the start of the human robot interaction, prior to commencement of any gesture recognition, the 3D model is calibrated to the person of interest. In particular, the model is initialized within the depth image of the person and verified by utilizing information from the *2D image* provided by the 3D camera, where any necessary scaling will take place. Any coordinate transformations of the model from hereon will be with respect to this original relaxed pose of the person.

2. Human Body Silhouette Identification

A binary-based background subtraction method is utilized to quickly and effectively determine and extract the boundaries of potential humans in the scene. The advantage of utilizing this method is that continuous boundaries of objects can be easily defined. Background subtraction, [13], regenerates the 3D grayscale image into a binary image in which 1 represents the foreground objects and the background is represented by 0. A threshold depth value can be set to separate these objects from the background in the 3D image. Once the potential foreground human, Fig. 3(a), has been determined based on depth information, an edge detection method is implemented to effectively identify the human silhouette, Fig. 3(b). The Canny-Deriche edge detection algorithm is used in our work to determine potential boundaries by identifying edge pixels via gradient intensity [14].

3. Lower Arms and Head Identification

Human skin can be distinguished in thermal images due to the thermal properties of the body. By using thermal images, Fig. 3(c), the exposed lower arms and head of a human can be identified and consequently the transformation of these body parts can be estimated. This transformation can be utilized to identify the body gestures of the person. Since the 3D image does not provide enough information to directly detect the arms and head locations, we propose the use of thermal images to assist in identifying the arms and head locations. This is done by extracting arm and head positions by performing temperature-based segmentation on the thermal image, Fig. 3(d).

Since there is a calibrated correspondence between the thermal and 3D images, the identified location of the lower arms and head in the thermal images can be utilized to identify their location in the 3D depth images.

Body Part Transformation

3D data information is then extracted from regions of interest along the arms in order to determine their pose during a particular gesture. Within these regions $\boldsymbol{n}$ points are sampled, where $\boldsymbol{n}>5$. The $\boldsymbol{n}$ sampled points define vectors along each forearm (mainly from the elbow to the fingers) which are then tracked as the person displays various gestures. The vector fitting within this area is generated via a skeleton-based approach. The transformation of the vector as each body part moves in 3D space is estimated to represent the rigid transformation of the corresponding body part: $\mathbf{T}(\alpha, \beta, \gamma, X, Y, Z)$. This allows for tracking of the arms from the relaxed pose to other poses during human-robot interaction.

4. Upper Arms and Upper Trunk Identification

Once the location of the lower arms and head are estimated, via thermal images, the location of the upper trunk and upper arms can then be estimated by using the 3D model. The articulated 3D model is fit to the 3D range information for which the silhouette and the location of the lower arms and head have been identified. The model is then used to identify the location of the upper trunk and upper arms. More detailed 3D data information extracted from regions of interest on the 3D images can be utilized to better approximate the corresponding 3D model. In particular, these regions of interest include areas around potential joints and around the central axis/axes of the body parts to detect change in depth along the body part. The central axis can be defined as an axis about which orientation occurs. Hence, with the utilization of the 3D depth information, we can approximate the location of the occluded and non-occluded body parts and approximate the appropriate 3D model, Fig. 2(e). In particular, since the motion parameters to be determined can be within a large range, a rough estimation is only needed to approximate the model. In summary, by using depth segmentation and knowledge-based algorithms, the remaining body parts can be identified and their corresponding transformations, **T**, estimated.

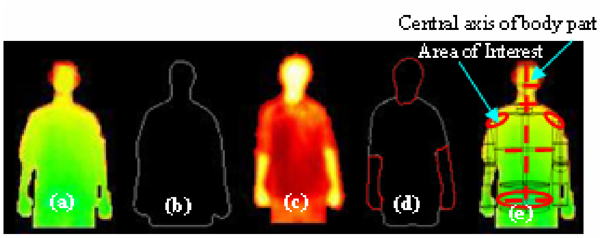


Fig. 3: (a) 3D image, (b) silhouette from 3D image, (c) thermal image, (d) temperature-based segmentation from thermal image, and (e) 3D model matching to 3D image.

3. CONTROL ARCHITECTURE

The proposed control architecture as presented in [15] is adapted and extended from the Cognition and Affect (Cogaff) information processing architecture. 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 remaining modules of the architecture consist of the drives module and a robot emotional state module, which are utilized to identify the tasks the robot needs to complete and to assist in behavior selection, Fig. 4.

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 includes the affective state of the person interacting with the robot (as defined herein by gestures and classified by the Human Mood Classifier Module) and the robot's internal/external sensory information. The robot's tasks are stored in the long term memory module, Fig. 4. 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 robot emotional state module, 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, and (ii) the emotional state of the robot is failing to complete the required task. For example, 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.

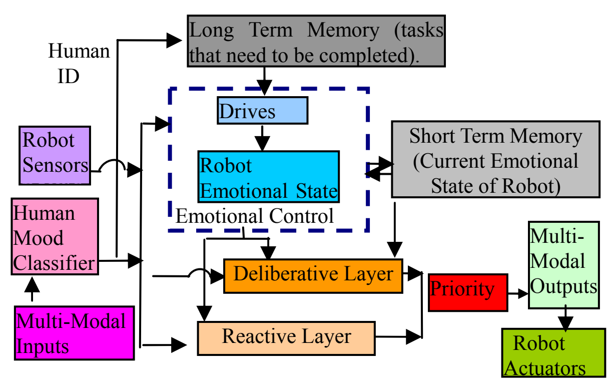


Fig 4: Proposed Control Architecture [15].

Although there have been a number of emotional behavior architectures proposed in the literature [i.e., 16,17], 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. [18], Fig. 1.

An assistive robot's behavior should reflect the task it needs to complete and its emotional state should 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. In this paper, we present the design of the mood classifier and the deliberative layer.

HUMAN MOOD CLASSIFIER

The gestures that will be identified via our proposed gesture recognition technique are derived and modified accordingly to the Davis Nonverbal States Scale (DNSS) [19]. DNSS is a coding method designed to analyze the gesticulations displayed by a person in a one-on-one conversation. Within the DNSS, we utilize and adapt the Nonverbal Interaction and States Analysis (NISA) scale to code the recognized gestures into a person's position accessibility level. The scale consists of 4 levels of accessibility ranging from Level I (least accessible) to Level 4 (most accessible), which are categorized by the body trunk and arms patterns such as towards (T), neutral (N) or away (A) from the robot. 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 to 15 degrees, and Away-where the trunk is oriented more than 15 degrees 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 interactions and will repeat these gestures during the course of the interaction.

DELIBERATIVE LAYER

In interactive situations, it is difficult to model and predict the potential events that will occur between humans and robots. 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., 20-22], but has yet to be applied and adapted to the field of human-like task driven 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.

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 [23]. 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) [23].

Since human actions can be unpredictable when interacting with the robot, a nondeterministic Q-learning scheme is investigated for task-driven socially assistive robots, where rewards are represented by probability distributions, Fig. 5. Each state is defined by the accessibility level y_{Hi} of the person, the robot's emotional state y_{Ri} and the drive d_i that needs to be satisfied. The assistive robot starts in an current state: i.e., $s_0(y_{Hi}, y_{Ri}, d_i)$, and will perform an action (which results in the maximum Q value) that will lead it to satisfy its dominant drive, d_i. For our Q-learning approach, each state has 4 actions that can be implemented. Due to the uncertainty of the interaction, the drive may or may not be satisfied. If Action 1, denoted by a_1 in Fig. 5, is implemented and the drive is satisfied, the robot will reach state s_1, ready to perform a new set of tasks. s_1 will consist of updated information regarding the robot's emotional state, the person's accessibility level and the next drive that needs to be satisfied (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 [24]:

$$Q_n(s,a) = r(s,a) + \gamma \sum_{s'} P(s'|s,a) \max_{a'} Q_n(s',a'), \qquad (1)$$

where $r(s,a)$ is the immediate reward function and is determined by $r(s,a)=w*r_{di}$. Where w is a weight determined from the accessibility level of the person and r_{di} is a reward represented by the drive that needs to be satisfied. The value of r_{di} increases as the robot approaches its final drive. 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.

The training rule we utilize to assure convergence of $\hat{Q}$ (learner's approximation) to Q is defined by:

$$\hat{Q}_n(s,a) \leftarrow (1-\alpha_n)\hat{Q}_{n-1}(s,a) + \alpha_n[r(s,a) + \gamma \max_{a'} \hat{Q}_{n-1}(s',a')] \quad , \quad (2)$$

where,

$$\alpha_n = \frac{1}{1 + visits_n(s,a)} \quad . \tag{3}$$

visits(s,a) in Equation (3) represents the number of times action a has been selected while the robot is in state s. α_n is a learning rate which decreases after time to allow for convergence.

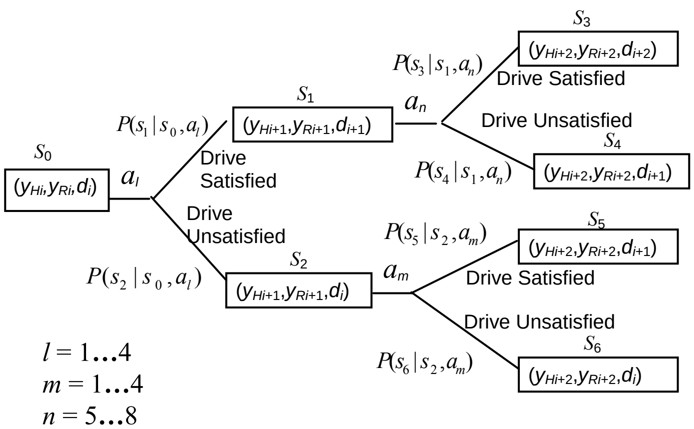


Fig. 5: Learning-Based Model.

4. EXPERIMENTS

Our experiments consisted of the robot, Brian, and a human interacting in a one-on-one conversation standing approximately 1m apart, Fig. 6. Brian consists of a human-like demeanor having similar functionalities to a human from the waist up. 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 total, 30 human subjects participated in the experiments ranging in age from 17 to 68 years. Each human was asked to implement a number of predefined gestures for perception, identification and categorization into appropriate accessibility levels by the human mood classifier. These accessibility levels were utilized as inputs into the deliberative layer in order to identify the robot's behavior.

ROBOT PERCEPTION

In these experiments, the human was asked to implement a number of predetermined gestures for the robot to perceive. In order for the thermal camera to clearly identify the location of the arms, all subjects either wore short sleeves or sleeves that were rolled above their elbows. 3D and thermal images of the human were taken, and analyzed using the proposed gesture identification technique. Fig. 7 presents five typical gestures of a person in a: (i) towards position (with respect to the robot) where the body is upright and the arms are to the sides of the trunk, (ii) leaning forward with arms to the side of the trunk, (iii) leaning forward with arms crossed, (iv) towards position with arms up, and (v) towards position with arms in an X configuration. The human body silhouette was identified using background subtraction on the 3D depth images. Then the location of the lower arms and head in the 3D images were determined via thermal-based segmentation in the thermal images. Vectors of depth points were identified on the forearms of each person and were tracked during gesticulation. These vectors were utilized to identify the transformation of each arm from the relaxed towards position, i.e., Fig. 7(a), with respect to the global coordinate frame. The transformation results for the gestures depicted in Fig. 7 are presented in Tables 2 and 3.

Once the location of the head and lower arms are identified in the 3D images, an approximate articulated 3D model was fit to each 3D image and was utilized to estimate the pose of the upper trunk via sampling of points in interest regions and around the central axis/axes of the body parts to detect change in depth along each body part, i.e. Fig. 8. This depth information was utilized to identify the appropriate transformations of the upper trunk and hence, to better approximate the corresponding 3D model. Transformation results for the two different trunk poses depicted in Fig. 7 are presented in Table 4.

In addition to the towards and lean forward positions, two more poses which consisted of the orientation of the person's upper body to be away from the robot were also tested to verify the proposed technique, Fig. 9. The determined transformations for these two poses are presented in Table 5.

The accessibility levels for all the identified gestures presented in Figs. 7 and 9 were determined and shown in Table 6. These accessibility levels were then utilized as inputs into our deliberative layer.

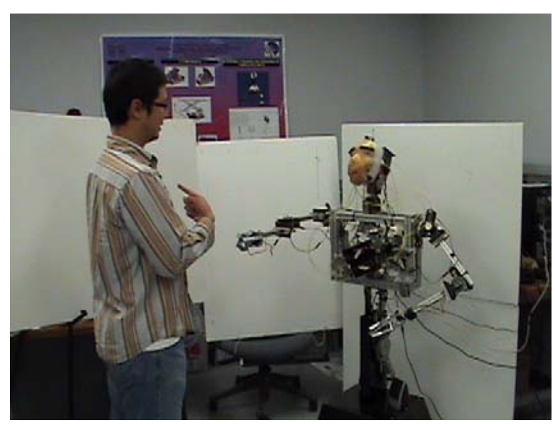
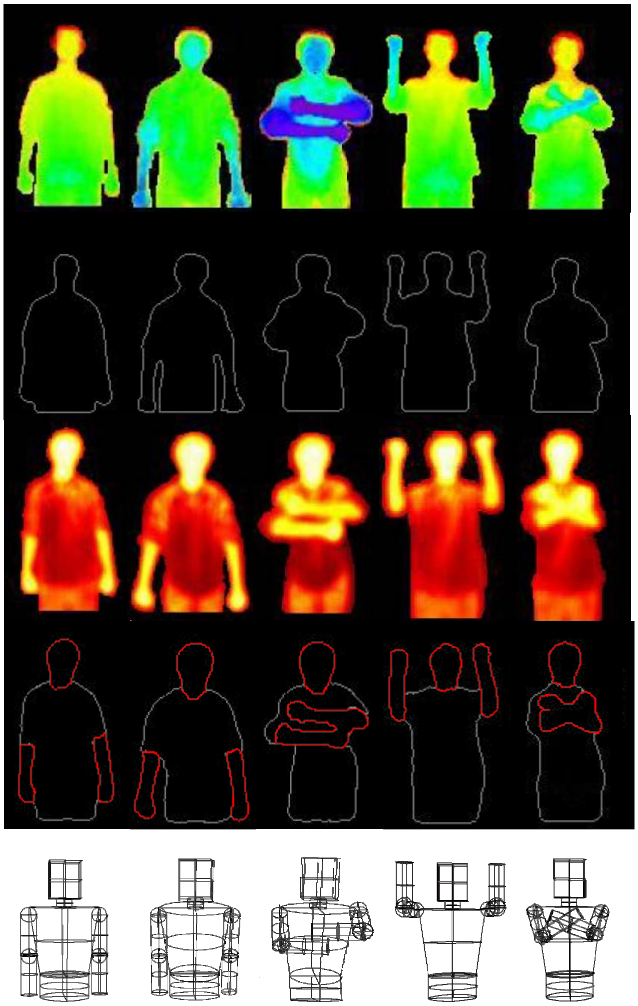


Fig. 6: One-on one interaction scenario with the robot Brian and a human.



(a) (b) (c) (d) (e)

Fig 7: (a) Towards Position, (b) Lean Forward Position, (c) Lean Forward with Arms Crossed, (d) Towards Position with Arms Up, and (e) Towards Position with Arms in an X Configuration.

Table 2: Transformations of Left Arm from Towards Position to the other 4 Identified Positions in Fig. 7.

	Fig. 7(b)	Fig. 7(c)	Fig. 7(d)	Fig. 7(e)
α (deg.)	-9.73	-97.91	-173.46	-133.88
β (deg.)	-4.47	5.25	-4.16	13.55
γ (deg.)	-7.70	-7.87	-21.44	-8.32
ΔX (cm)	10.48	11.57	10.91	38.66
ΔY (cm)	-30.08	36.92	50.09	38.12
ΔZ (cm)	-5.84	-11.79	-5.15	-8.87

Table 3: Transformations of Right Arm from Towards Position to the other 4 Identified Positions in Fig. 7.

	Fig. 7(b)	Fig. 7(c)	Fig. 7(d)	Fig. 7(e)
α (deg.)	5.02	82.16	160.74	118.9
β (deg.)	-0.65	3.09	23.70	9.25
γ (deg.)	-1.93	-14.04	-17.23	-1.75
ΔX (cm)	1.32	4.20	18.02	-33.59
ΔY (cm)	-8.42	15.17	19.62	-12.68
ΔZ (cm)	-1.41	-7.72	-1.27	-13.77

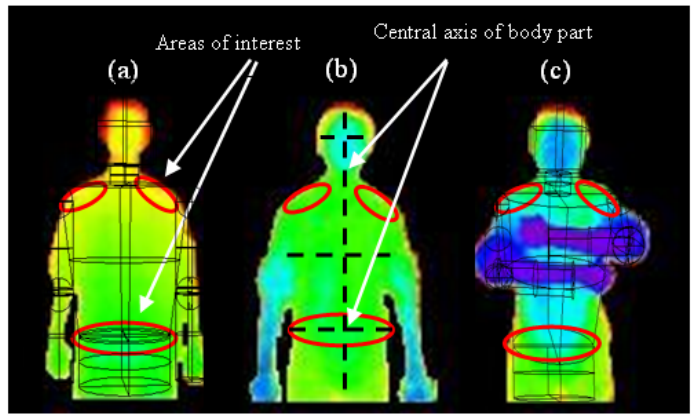


Fig. 8: (a) Areas of Interest; (b) and (c) Areas of Interest and Central Axis of Body Part.

Table 4: Transformations of Upper Trunk from Towards Position to the other 2 Identified Positions in Fig. 7.

	Fig. 7(b)	Fig. 7(c)
α (deg.)	-3.05	-2.75
β (deg.)	-5.88	-7.25
γ (deg.)	-15.66	-15.42

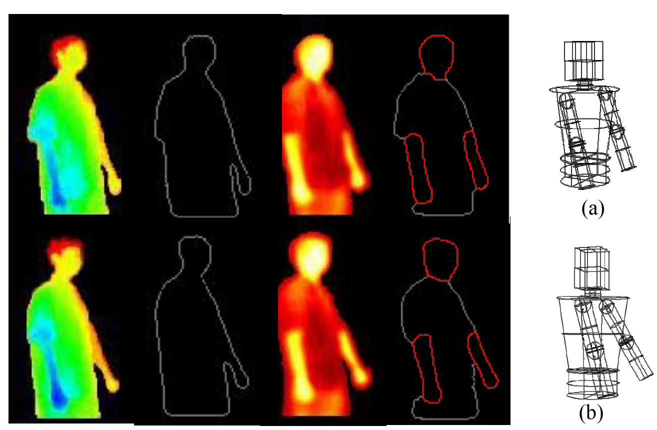


Fig. 9: Away Orientation: (a) Orientation 1 and (b) Orientation 2.

Table 5. Transformations of Upper Trunk from Towards Position to the other 2 Identified Positions in Fig. 9.

	Fig. 9(a)	Fig. 9(b)
α (deg.)	-7.46	-7.62
β (deg.)	-39.99	-47.29
γ (deg.)	5.19	-0.56

Table 6. Accessibility Levels.

Gestures	Accessibility Levels
Fig. 7(a)	IV
Fig. 7(b)	IV
Fig. 7(c)	III
Fig. 7(d)	IV
Fig. 7(e)	III
Fig. 9(a)	I
Fig. 9(b)	I

DELIBERATIVE LAYER

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 activity reminders to the person: (i) when to go for a walk, (ii) take necessary medication and (iii) go to a doctor's appointment. In addition, a companionship drive is also used in which the robot engages in a social interaction scenario with the person. For these experiments, the emotional states of the robot were defined as happy, neutral, sad and anger. These emotions were determined based on a priority look-up table. A database of four potential robot behavior actions for each state was also created. We utilized a discount factor of $\gamma = 0.8$.

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 drive. If the drive was not satisfied, the person would say "no" and the robot would continue to try to satisfy the drive. Figs. 10-12 present our experimental results.

From Fig. 10 it can be seen that it took 2 to 3 iterations to satisfy the robot's required drives. In general the robot was able to satisfy all four drives in the dominant emotional state of happy, Fig. 11. The second most dominant emotional state was neutral followed by sad. What is interesting to note is that the robot was able to satisfy its drive, drive #3, only once (out of 26 times) when it was angry. When assessing the accessibility levels of a person during interaction with the robot, it can be deduced that when the person was in accessibility level IV, a greater number of drives were satisfied, Fig. 12. If the person was in a lower accessibility level such as accessibility level II, the robot was still able to satisfy the drives a significant number of times.

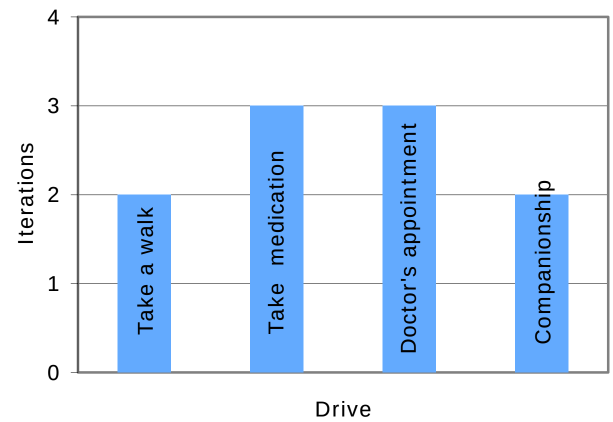


Fig. 10: Drive versus Iteration.

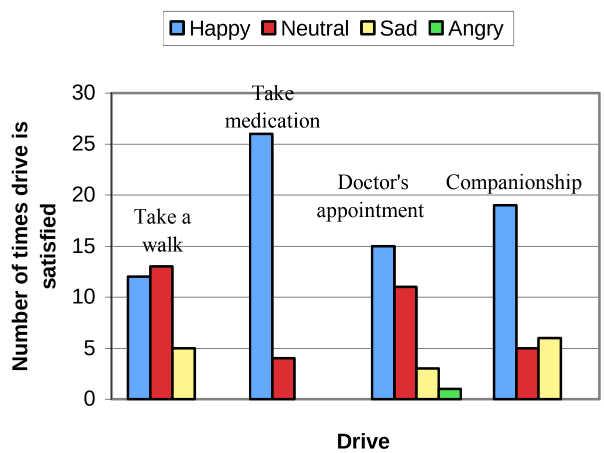
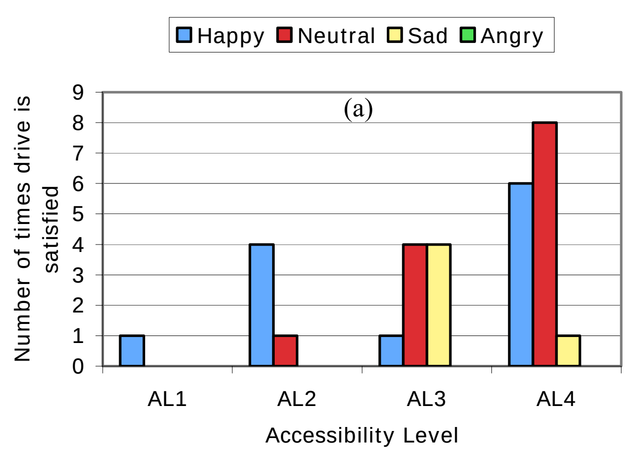


Fig. 11: Drives versus Robot's Emotional State.



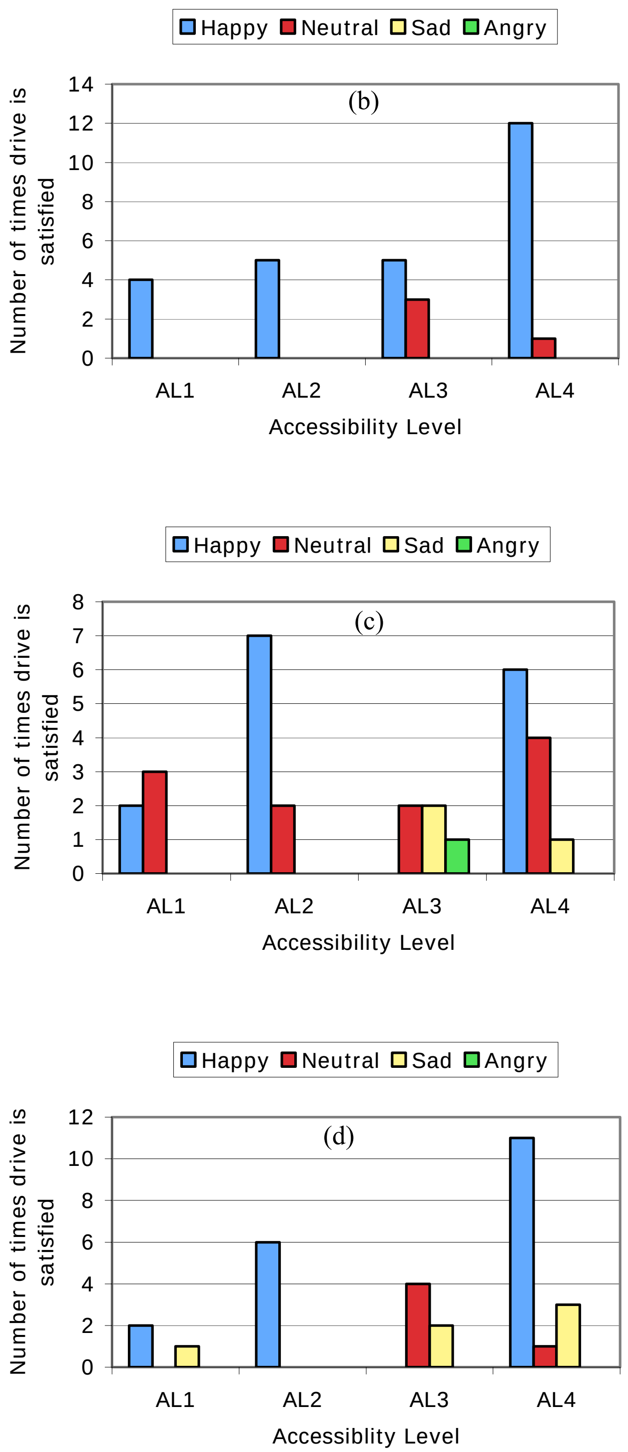


Fig. 12: Human's Accessibility Level versus Robot Emotional State for: (a) Drive 1, (b) Drive 2, (c) Drive 3, and (d) Drive 4.

5. CONCLUSIONS

This work mainly focuses on developing a novel gesture recognition, identification and classification technique capable of tracking and interpreting human gestures and body language as semantically meaningful commands for input into a unique multi-layer decision making control architecture. Depth and thermal images from a 3D camera and a thermal camera are used for visual perception of gestures and characterization. A learning-based control architecture is presented in which the deliberative layer determines the effective and appropriate task-driven behavior of the assistive robot. The categorized gestures are utilized by the control architecture to determine the affective state of the person during interaction. The preliminary experiments verified the potential of the proposed method in unknown assistive human-robot interaction environments. Our future work includes extending the proposed recognition technique to cluttered environments and developing processing mechanisms for the remaining modules in the control architecture and expanding the architecture to incorporate multi-modal inputs from the human, i.e., speech and facial expressions in addition to gestures.

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