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Adapting Robot Behavior for Human–Robot Interaction

[1.] G.John Christopher, [2.]S.Preethi and [3.]S.Jailani Beevi

[1,2,3] Periyar Maniyammai University, Thanjavur-Tamilnadu, India

[1]g.johnchrist@gmail.com [2]twistedpreethi@gmail.com [3] friends4ever.beevi@gmail.com

Abstract: Human beings subconsciously adapt their behaviors to a communication partner in order to make interactions run smoothly. In human–robot interactions, not only the human but also the robot is expected to adapt to its partner. Thus, to facilitate human–robot interactions, a robot should be able to read subconscious comfort and discomfort signals from humans and adjust its behavior accordingly, just like a human would. We propose an adaptation mechanism based on reinforcement learning that reads subconscious body signals from a human partner, and uses this information to adjust interaction distances, gaze meeting, and motion speed and timing in human–robot interactions. The mechanism uses gazing at the robot's face and human movement .Distance as subconscious body signals that indicate a human's comforted discomfort. A pilot study with a humanoid robot that has ten interaction behaviors has been conducted. The study result of 12 subjects suggests that the proposed mechanism enables autonomous adaptation to individual preferences.

Keywords: Behavior adaptation, human, interaction

1. Introduction:

The idea of teaching a machine human-intelligence may be traced back to Turing's original thoughts of an intelligent machine. To approach the challenging problem of teaching a computer human-intelligence, a computer-controlled multisensory mobile robot is used in this project to interact with human when a human teaches the computer, and the spoken language acquisition research is selected as the first subproject. The terminology of "spoken language acquisition" denotes the process of a computer to learn the signal pattern and the meaning of human speech. The spoken language acquisition research has two advantages over the whole project. First, the computer's speech ability can help developers to retrieve what the computer has learned in a. In our project, the algorithm uses the robot sensory inputs instead of text to explain speech signals so that the robot can learn speech in various (potentially any) languages.

1.2. Information Theory Analogy of the Robot Training Process

The robot training process can be considered as an information transmission process. In this process, the human teacher is considered as an information source. All sensors on the robot platform are considered as a communication channel. The robot brain (i.e. the computer) is considered as an information destination.

With this analogy, the information distribution in a sensory data feature space is vital for the robot training and the algorithm design. Let x be a point in the feature space, y be a possible label x, and p (y|x) be the conditional probability of y at point x, the information related to point x can be measured with conditional entropy

(1) As ***p (y|x)*** varies in the feature space, the information related to every feature point also varies in the feature space. If two
Classes' ***y1*** and ***y2*** are separated based on the Bays decision theory,
(|) (|) 1 2 *p y x* . *p y x* (2)

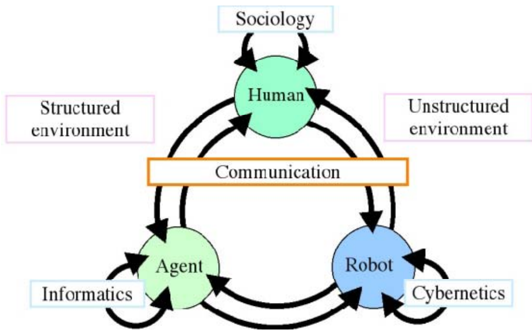

Figure.1 Communication between Human -Robot.

Communication among a human, a computer agent, and a robot. Will hold at a boundary point x of class y1 and class y2. (2) Indicates that the boundary points have more information than other points. Based on this fact, a robot instructor should spend most teaching effort on data that are close to a decision boundary. Brain should assign sufficient resources to learn the data that are close to a decision boundary. When a robot responds correctly to its input, the robot teacher should consider that the robot have understood the training sample and therefore do nothing to the When the robot responds incorrectly to its input, the teacher should consider that the robot does not understand the training sample and therefore should repeatedly teach the robot about the correct response to the sample. This training scheme is different from the classical training scheme, in which the classifier parameters are estimated only according to the data. Frequency in real life and no additional trainings are done for misclassified cases.

The cell that has a high ***IR*** estimation into two to increase resources in the region. In real implementation, the threshold _ of ***IR*** for cell separation is dynamically changed according to the available resources.

A. Adapted Parameters

We adopted six parameters to be adapted by the system. These were three interaction distances (intimate, personal, and social distances) for three classes of proxemics zones, the extent to which the robot would meet a human's gaze (gaze-meeting-ratio),waiting time between utterance and gesture (waiting-time), and the speed at which gestures were carried out (motion-speed).

B. Reward Function

The reward function is based on the movement distance of the reward function is based on the movement distance of the human and the proportion of time spent gazing directly at the robot in one Interaction. It had a positive correlation with the length of the gazing time and a negative correlation.

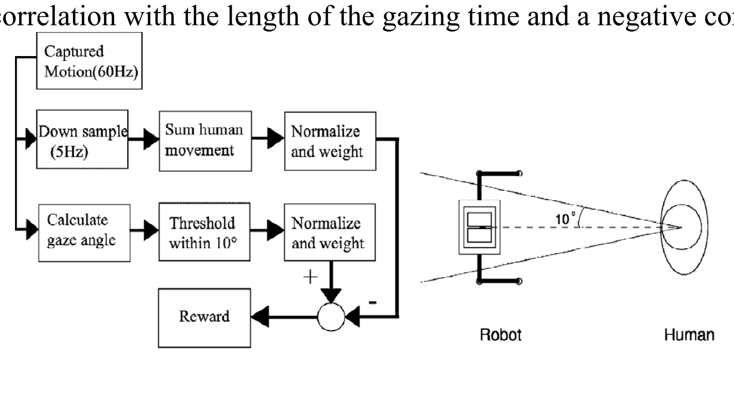

Figure.2

(a) Block diagram to calculate the reward function. The 3-D-position

Data captured by a motion capture system at 60 Hz are down-sampled to a 5Hz sampling rate. They are used to calculate the human movement distance and gazing period. They are then normalized, weighted, and summed

(b) Angular interval determined as human gazing at the robot is ±10◦.The reward function R is defined as

$R = -0.2 \times$ (movement distance (millimeters))

$+ 500 \times$

(Time human spent looking at robot)/

(Time spent for the interaction behavior)

Interaction Behaviors of the Robot

Each behavior took about 10 s to run. The robot always initiates the interaction like a child who asks to play since its concept is a child-like robot. We classified interaction behaviors into Hall's three interaction categories [1]: intimate (0–0.45 m); personal (0.45–1.2 m); and social (1.2–3.6 m) by another restudy. It also meets the human's gaze in a cyclic manner, where the robot meets and averts the human's gaze in cycles that last 0–10 s (randomly determined, average 5 s), as this is the average cycle length for gaze meeting and averting in human–human interactions.

The waiting-time controlled how long the robot would wait between utterance and action. When it performs behaviors from (a) hug to (g) monologue that require motion on the part of the human, the robot starts actions after it makes an utterance (like "Please hug me," "Let's play rock–paper–scissors,"

And waiting-time has passed. The motion-speed controlled the speed of the motion. If motion speed is 1.0, the motion is carried out at the same speed as the gesture is designed to do. As for gaze-meeting-ratio, waiting-time, and motion speed, the same values are used for all interaction behaviors.

Interaction*:* The robot was initially placed in the middle of the measurement area, and the subject was asked to stand in front of the robot and interact with it in a relaxed, natural way. The robot randomly selected one of the ten interaction behaviors .After one behavior finished; it randomly selected the next one. The interaction lasted for 30 min. Except for controlling the selection not to repeat the same behavior twice in a row.

3) Adaptation*:* During the interaction, the adaptation system was running on the robot in real time. Table I shows the initial values and the search step sizes. The initial values were set slightly higher than the parameters that the subjects in the restudy preferred.

The duration starts from just after the robot selected the behavior or before it utters and it ends at the end of the behavior or just before the next behavior selection. A total of ten different parameter combinations were tried before the gradient was calculated and the parameter values updated ($T = 10$).

4) Preferences Measurement (Interaction Distances)*:* The subject was asked to stand in front of the robot, at the distance he/she felt was the most comfortable for a representative action for each of the three distances studied by using behaviors (a) hug, (c) handshake.

1.3. Experiments

We are presently using our algorithm to enable a mobile robot to learn spoken language through its interaction with humans. The system architecture is described in Fig. 2. In this system, we use a dual CPU Octane as the "brain" of the learning system. The multimodal robot platform is used for signal acquisition through many different sensors. These sensors include a video camera, 2 microphones, 4 tactile sensors, a digital compass, a tilt sensor, a temperature sensor, bumper switches etc. The robot platform. May also performs some actions through its propelling motor and steering motor. The Octane computer and the robot platform are connected through a pair of wireless modems and a pair of NTSC transmitter/receiver. Through these communication channels, the computer can request the robot to collect required signals with its multimodal sensors, or command the robot to move around

According to computer decisions.

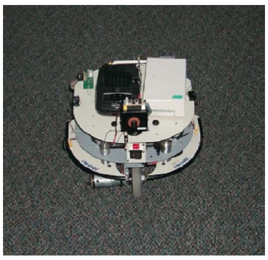

Figure 3. Touch sensors are installed on the robot chassis

1. Right sensor; 2. Back sensor; 3. Left sensor; 4. Front Sensor.

In this experiment, we teach the robot to move according to our command through pushing corresponding touch sensors. With these touch sensors; we can avoid damaging the robot motors by forcing them to move according to our commands. Since the robot only has two motors to drive the platform, we can only teach the robot 6 actions. These actions are “forward”, “back”, “straight”, “stop”, “left”, and “right”. They are directly related to the robot’s feeling on touch sensors. These commands and their associated touch feelings are taught to the robot through our interactions with the robot. For example, suppose we want to teach the robot the utterances “forward” and “back”.

At the beginning, the robot cannot decide if there is any difference in meaning between these two sounds. So, it is possible to move forward when we say “back”. This means that the feature vector of the utterance “back” locates a representation vector that has a different label, whose meaning is to instruct the robot to move forward. Our algorithm can recover from this problem in the following way. In this case, the right thing for us to do is to say “back” again to the robot, and label them. .If the robot cannot understand us, repeat the same word and label it again whenever possible. After the generation of the new cell, the computer will have more cells to represent the intensively taught data. The building of new Verona cells may increase the local resolution for distinguishing different inputs. After we teach the robot the semantic meaning of the new cell through touching related sensors, the robot should be able to distinguish the semantics of the utterances “forward” and “back”. It is still possible for the robot to misunderstand “forward” and “back”. With other sounds, but we can help clarifying these meanings through more interactions with the robot.

1.4. Expected Results

A. Adaptation Results

For most of the subjects, at least part of the parameters reached reasonable convergence to stated preferences within 15–20 min, or approximately ten iterations of the PGRL algorithm. We have excluded the results of three subjects who neither averted their gaze nor shifted position however inappropriate the robot’s behavior became, but showed their discomfort in words and facial expression to the experimenter. The bars show the interval for acceptable distance and the preferred value, and the asterisks (*) are the learned values. it shows the remaining three parameters, where circles (_) indicate what values the subjects indicated as preferred. Some subjects indicated a preference in between two values, and these cases are denoted with a triangle () showing that preferred value.

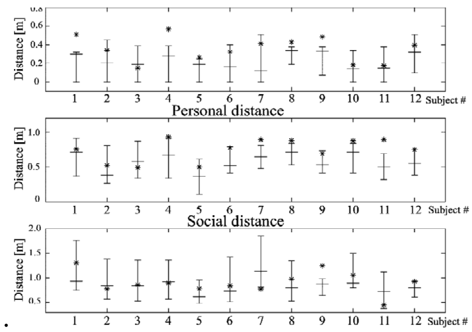

Figure 4

B. Case Studies: Adaptation Results and Subjects’ Impressions In the following, we show how the system behaved for different

1) Successful. 2) Partial success with content subjects. 3) Successful but discontent Subjects. 4) Partially successful but discontent subjects.

1) Successful Runs—Content Subjects: There were three subjects for whom the system performed very well. Not only were the subjects themselves content with the performance, but also all parameters displayed good convergence to their stated preferences. Common for all of them was a tendency to be very interested in interaction with the robot, and they had a very positive interaction pattern, much as when interacting with another human it was impressed by the robot’s behavior and said that it quickly became much better. The plots support this, as all parameters are adapted to the preferences, except *personal* distance, which is only slightly farther.

2) Partially Successful Run—Content Subjects: The next group consists of two subjects who were content with the robot’s behavior, even though analysis of the results shows that some parameters were far from stated preferences.

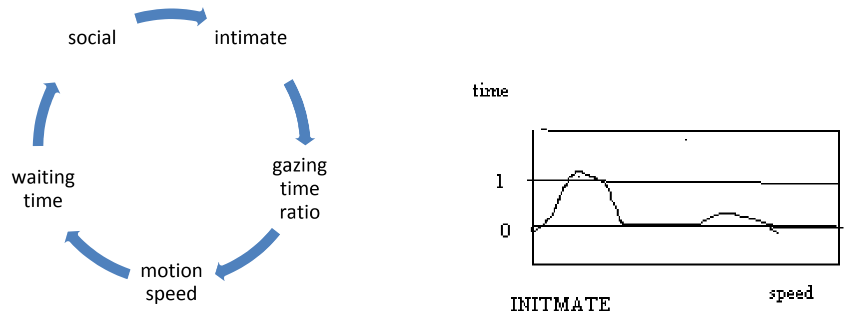

Figure 5. Process on adaptation

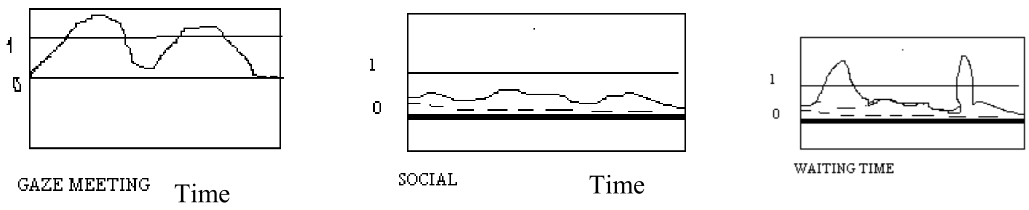

Figure 6.
The dashed lines Represent the most preferred Dotted lines represent the measured preferences of values.

3) Successful Run—Discontent Subject: She described her first impression of the robot's behavior as "tentative," but that it became more active as time passed. She also stated that she thought it tended to get too close, even though actual *intimate* and *personal* distances converged to her farther acceptable limits.
4) Partially Successful Runs—Discontent Subjects:. *Motion-speed* parameter was far away from the stated preference, something the subject also complained about. Observations of the actual study showed. That as the robot increased its *motion-speed*; the subject seemed towpath the movements carefully and fixes her gaze at it.

2. Summary and Future Work

In this paper, we present our work on spoken language acquisition. This work is the first subproject of our autonomous Learning robot project. The next step of the robot project is going to involve sound mimic experiments with the robot learning system. Providing the system with "speak back" ability will greatly increase the number of actions that a robot can perform. In the long run, we prepare to expend our learning framework to many other modalities, and enable the robot to express its sensory detection and internal state in speech and body motions. Moreover, we are also interested in applications that use the proposed framework to train home appliances. Natural language understanding makes the system easy to use, without the user having to know anything about robots, computers or programming.

3. Acknowledgement

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