EMOTION-SENSITIVE ROBOTS- A NEW PARADIGM FOR HUMAN-ROBOT INTERACTION

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Abstract

An emotion-sensitive human-robot cooperation framework where a robot is sensitive to the emotions of the human working with it and is also capable of changing its behavior based on this perception is presented in this paper. Peripheral physiological responses of a human are measured through wearable biofeedback sensors to detect and identify his/her underlying level of anxiety. A control architecture inspired by Riley's original information-flow model is designed. In this human-robot interaction framework, the robot is responsive to the psychological states of the human and detects both implicit and explicit communication from the human to determine its own behavior. Human-robot cooperation experiments using a mobile robot as a test bed are performed where the robot senses anxiety level of the human and responds appropriately. The results presented here validate the proposed framework and demonstrated a new way of achieving emotion based interaction between a human and a robot.

Keywords: emotion detection; physiological sensing; human-robot interfaces; personal and service robotics.

1. Introduction

In the fourth century B.C., Aristotle who is popularly credited with the original concept of automation [1] , wrote "If every instrument could accomplish its own work, obeying or anticipating the will of others…if the shuttle could weave, and the pick touch the lyre, without a hand to guide them, chief workmen would not need servants …" From the earliest implementations of clock based automatons in the early 14th century to "ASIMO" – one of the most advanced humanoid robot, the field of robotics has come a long way. The ever increasing applications of robots in all arenas of modern life are expected to usher in a new era where these smart autonomous systems will have significant impact on how we live our daily lives. Hence, the need for the robots to understand human intents and desires

– the unfulfilled part of Aristotle's vision, is becoming increasingly important. In this context, it appears that detecting and analyzing emotions and other affective states can be a useful indicator of human intent.

Over the years, the traditional impression of emotions as being maladaptive has changed to one of being functional. The latest scientific findings indicate that emotions play an essential role in rational decision-making, perception, learning, and a variety of other cognitive tasks [2]. Hence it appears that endowing the robot with a degree of emotional intelligence would open the doors to more meaningful and natural interaction between humans and robots. The current trend in human-robot interaction requires explicit communication from the human. A person communicates with a robot by either typing-in or (more rarely) speaking-out explicit instructions. Lately other modes such as, eye gaze, head motion, gestures, and EMG signals are also being used to command and control robots. Such modes of communication are generally effective in many applications; however, a human-robot interaction that relies solely on explicit communication ignores the potential gain of implicit communication. By implicit communication, we mean interaction in which the emotional states of the human are detected, interpreted and responded to, by the robot. This can also be referred to as "affective communication" since it involves identifying and recognizing affective or emotional states of the human. Given the crucial role theoretically ascribed to emotions in human social communication [3][4], the gains of endowing human-robot interaction with affective communication could be substantial.

There are numerous potential applications of emotion-sensitive robots. A robot that is capable of sensing emotional states like panic, fatigue, stress, and inattention could immediately take meaningful actions to help a human during search and rescue operations, fire fighting, space/remote planet/underwater exploration, and warfare. Rehabilitation robotics is yet another application of such versatile robots. Robotic devices for rehabilitation could use emotion-sensing capability to provide exercise sequences that are comfortable but still challenging for the patient. A prototype Nursebot [5] was very recently introduced by CMU and the University of Pittsburgh to help the elderly by reminding them when to take medicine, monitoring for falls, and providing a video stream to a remote observer. An emotion sensing potential would augment the utility of such healthcare robots. Other applications in this domain might include industrial robots that can sense the fatigue of the workers on the shop floor and take necessary precautions to avoid accidents. The robotic toys industry could also benefit from such research where a robot that could understand and respond to the emotions of a child could be an extraordinarily engaging plaything. All these potential applications would eventually lead to the development of personal robots, which will act as understanding companions of humans in the future.

In this paper we have designed and implemented a novel human-robot interaction framework that draws on promising results from the fields of affective computing, psychology and robotics. The aim was to develop an emotion-sensitive robot (Oracle) that (i) detects and identifies anxiety levels of the human that it worked with, (ii) combines implicit and explicit communication from the human in order to detect the urgency of the human's requirements, and (iii) alters its behavior dynamically and intelligently according to the changing environment.

The current work builds on our initial work done in this area [6]. We have used an information flow based architecture inspired by Riley's work [7] in which Oracle uses psychological state information from a human to formulate and execute an action plan. This architecture enables Oracle to combine implicit and explicit communication from the human to determine the urgency level of any situation. Oracle then changes its behavior in order to adapt to the changing environment.

The paper is organized as follows: Section 2 describes the rationale behind employing physiological signals for emotion detection. A brief discussion on emotion detection and recognition procedure is presented in Section 3. Section 4 and Section 5 present the main contribution of the paper which includes the behavior based architecture described above, experimental setup and the results. Finally, Section 6 summarizes the contribution of the paper and provides important conclusions.

2. Physiological Responses for Emotion Recognition

Emotions are patterns of reaction that include physiological changes, expressive behaviors, and states of feeling [8]. There are various indicators of emotion that can be exploited to identify affective states, for instance- facial expressions, gestures, vocal intonation, physiology etc. A detailed literature review to encompass affect recognition from all types of external observations is too broad to be included here. As a result, we have cited few important works in the field with more emphasis on affect recognition from physiological signals. Work by Reeves and Nass [9] provided a new outlook on how people interact with computer. Picard's work pioneered the field of affective computing [2]. Change in emotion has been considered either along a continuous dimension (e.g., valence or arousal) or among discrete states in the literature. Rule-based system has been used in facial expression recognition [9]. Fuzzy logic has been used for emotion recognition from facial expression [10], and from both facial and vocal data [12]. Fuzzy logic has also been used to detect anxiety from physiological signals by our group [13], and by [14]. There are several works on emotion detection from speech based on k-nearest neighbors algorithm [15], linear and nonlinear regression analysis [16]. Discriminant analysis has been used to detect discrete emotional states from physiological measures [18]. A combination of Sequential Floating Forward Search and Fisher Projection methods was presented in [18] to analyze affective psychological states. Neural networks have been extensively used in detecting facial expression [19], facial expression and voice quality [20], and emotion in speech [21]. [22-23] used facial expressions, vocal intonation, and physiological signals for affect recognition. We have used adaptive neuro-fuzzy technique for emotion detection [24].

Bayesian approach [26] to emotion detection is another important analysis tool that has been used successfully. In [27-28], a Bayesian classification method has been employed to predict the frustration level of computer users based on the pressure signals from mouse sensors. Naïve Bayes classifier was used to predict emotions based on facial expressions [29]. [30-31] employed a Bayesian network to determine the user's affective state and personality characteristics from facial and speech data including choice of words, speech features, input style characteristics, and body language movements. [32-33] provided a dynamic Bayesian network model for recognizing students' emotion in educational games. In [34], a cognitive-affective model of users based on Dynamic Bayesian Networks (DBNs) and an ACT-R model [35] has been developed. Some other applications of Bayesian classification include modeling and recognizing human behaviors in a visual surveillance task [36], psychological assessment and modeling of students [37-38], determining cognitive load and time pressure from speech [39]. Hidden Markov Model based emotion detection was also investigated [40].

In addition, there is a rich history in the human factor and psychophysiology literature to understand occupational stress [41], operator workload [42], operator effort [43], mental effort [44] and other similar measurements based on physiological measures such as EMG, EEG, and heart rate variability (HRV). Attentional modulation of HRV was also observed during cognitive tasks [45]. A real-time system to determine mental strain in machine operation using biological signals was proposed in [25]. Multiple psychophysiological measures such as HRV, EEG, blink rates and others have been used together in recent years to assess pilots' workload [46]. Heart period variability (HPV) has been shown to be an important parameter for mental workload relevant for human-computer interface (HCI) [47]. Wilhelm and his colleagues have worked extensively on various physiological signals to assess stress, phobia, depression and other social and clinical problems [48-49].

The above literature survey, although brief, clearly indicates the tremendous potential of research that seeks to determine the psychological states. However, it must be noted that this field is fairly new and there are many unsolved problems pertaining to affect recognition in terms of algorithmic issues as well as choice of measures and their reliability. There are many application domains that have not been investigated yet but could benefit from this research. Our humble effort is designed to address some these issues.

We focused on using physiological responses as these are generally involuntary and less dependent on culture, gender and age than the other indicators of emotion. They offer an opportunity for recognizing emotions that may be less intuitive for humans but more appropriate for robots, which can acquire the physiological signals in real-time and employ various signal processing and pattern recognition techniques to infer the underlying emotional states. Recent innovations in *affective computing* [16] and *wearable computers* have made it feasible to process physiological signals using small and lightweight biofeedback sensors that are non-invasive, user-comfortable, unobtrusive, and fast enough for real-time applications [50].

There is good evidence that the physiological activity associated with affective state can be differentiated and systematically organized. Emotions are closely associated with the autonomic nervous system (ANS). ANS regulates the body's internal environment. It is composed of the sympathetic branch, which generally functions in emergency situations, and the parasympathetic branch, which dominates during periods of relaxation. The transition from one emotional state to another, for instance, from relaxed to anxious state is accompanied by dynamic shifts in indicators of ANS activity. The physiological signals we examined are: various features of cardiovascular activity [53], including interbeat interval, relative pulse volume, and pulse transit time, electrodermal activity (tonic and phasic response from skin conductance [54][55]) and electromyogram (EMG) activity (facial activity including activity of the corrugator supercilii [eyebrow] and masseter (jaw), [56]). These signals have been selected because they can be measured non-invasively and are relatively resistant to movement artifact. Table 1 shows the physiological responses that were selected and the various features that were derived from each response. Various signal processing techniques such as Fourier transform, wavelet transform, thresholding, and peak detection, were used to derive the relevant features from the physiological signals. All these features are powerful indicators of the underlying emotional state of the person showing this response. We have exploited this dependence of a person's physiological response on emotions to detect and identify emotions in real-time using advanced signal processing techniques.

3. Emotion Detection and Recognition

Various methods of extracting physiological patterns corresponding to emotional states exist but efforts to identify the generic signatures have not been largely successful due to person-stereotypy and situation-stereotypy [57][58]. That is, within a given context, different individuals express the same emotion with different characteristic response patterns (person-stereotypy). In a similar manner, across contexts the same individual may express the same emotion differentially, with different contexts causing characteristic responses (situation-stereotypy).

In the present work we have focused on detecting and identifying the emotion of anxiety. The goal was to represent each individual's anxiety index (a number on the nine-point scale indicating subjective anxiety level) as an approximate function of the physiological responses (features derived from cardiac activity, electrodermal activity, electromyogram activity).

A fuzzy logic based classification system that employs the physiological responses of a person to detect the corresponding level of anxiety has been discussed in detail in previous papers [6][59]. The novelty of the fuzzy logic based affect-recognition system was that it was both individual- and context-specific and accommodated the differences encountered in expression of emotions.

A series of tasks involving sensory-motor coordination was designed to elicit emotional responses from subjects. These included anagram solving, mathematical problem solving and auditory discrimination tasks. Using these experiments initially, we obtained pilot data to design and train an *n*-input 1-output fuzzy logic system.

- Input set = {$Power_{sym,}$, $Power_{parasym}$, IBI_{mean} and other features from Table 1}
- The *n* features constituting the input set were the ones significantly correlated with anxiety index.
- Output set = {*anxiety index*}
- The membership functions used: Gaussian

Table 1. Physiological responses and their features

Physiological Response	Features derived	Label used	Unit of measurement
Cardiac activity	Sympathetic power	$Power_{sym}$	Unit/Square Second
	Parasympathetic power	$Power_{parasym}$	Unit/Square Second
	Mean IBI	IBI_{mean}	Milliseconds
	Std. of IBI	IBI_{std}	Milliseconds
	Mean BVP	BVP_{mean}	Micro Volts
	Std. of BVP	BVP_{std}	Micro Volts
	Mean pulse transit Time	$Transit_{mean}$	Milliseconds
Electrodermal activity	Mean tonic activity level	$Tonic_{mean}$	Micro-Siemens
	Slope of tonic activity	$Tonic_{slope}$	Micro-Siemens/Second
	Mean phasic activity	$Phasic_{mean}$	Micro-Siemens
	Maximum phasic activity	$Phasic_{max}$	Micro-Siemens
	Rate of phasic activity	$Phasic_{rate}$	Response peaks/Second
Electromyographic activity	Mean - corrugator activity	Cor_{mean}	Micro Volts
	Std. of corrugator activity	Cor_{std}	Micro Volts
	Mean of masseter activity	Mas_{mean}	Micro Volts
	Std. of masseter activity	Mas_{std}	Degree Centigrade
Temperature	Mean temperature	$Temp_{mean}$	Degree Centigrade
	Slope of temperature	$Temp_{slope}$	Degree Centigrade/Second

In this paper we have used adaptive neuro-fuzzy inference techniques to learn information about the data set. This enabled us to determine the membership function features that best allowed the associated fuzzy inference system to predict the anxiety level, given a set of input physiological features. This learning technique resembles neural network learning. The Fuzzy Logic Toolbox of Matlab [60] was used to obtain tuned membership functions for optimal fuzzy inference. The features associated with the membership functions were computed using a gradient vector that indicated the ability of the fuzzy inference system to accurately model the input/output data for a given set of features. Once the gradient vector was obtained, backpropagation form of the steepest descent method was applied in order to adjust the features so as to reduce the mean squared error performance function. The backpropagation learning updated the network weights and biases in the direction in which the performance function decreases most rapidly - the negative of the gradient.

The network used for training had the following structure:

- *Network type*: Feed-forward backpropagation
- *Training function*: train_{lm} (A network training function that updates weight and bias values according to Levenberg-Marquardt optimization)
- *Adaptive learning function*: learng_{dm} (A gradient descent with momentum weight and bias learning function)
- *Performance function*: Mean squared error
- *Number of layers*: 2
- *Number of neurons in each layer*: 8

4. Control Architecture

For a peer level human-robot interaction to mimic similar human-human interaction, it is essential that both the robot and the human have implicit as well as explicit communication with each other. By the way of explicit communication the human and the robot can send information to and fro regarding the goals, tasks to be performed, the current task being executed and other such issues.

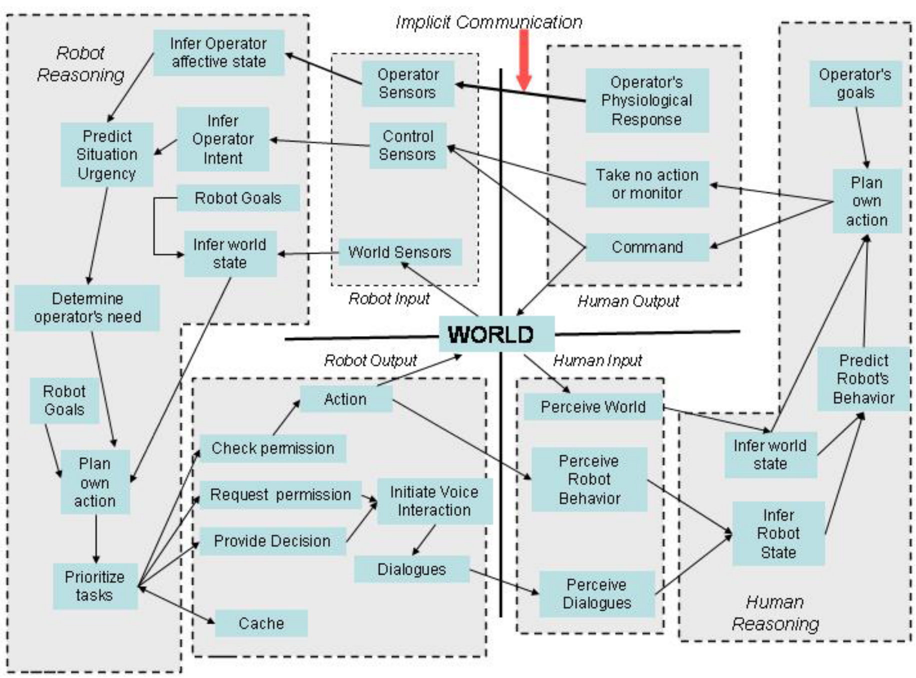

Figure 1. Human-Robot Interaction Architecture

By means of implicit communication, the robot can detect the emotional states of the human, use context based reasoning to infer the human's state, and take steps to assist the human. In order to facilitate such a naturalistic and intuitive collaboration between humans and robots, it is essential that the robot and the human behave as partners and take initiative in helping each other as well as achieving the common goal. This requires a systematic information flow between the human, robot and the environment. A generalized model of human-machine system developed by Riley [7] represents such an information flow that can be systematically modified according to any rule base to represent a particular level of automation in human-machine interaction. It is a powerful front-end analysis method that can be employed to identify human-machine protocols as well as the automation concerns that accompany the design of such systems. The general model represents the most complex level of automation embedded in the most complicated form of human-machine interaction. The model was altered to represent the specific system developed for human-Oracle interaction. This system mimicked a typical exploration setting where, a human and Oracle worked together in an unknown environment to explore a given region. In this case Oracle is expected to behave as an intelligent partner to the human. This requires Oracle to respond appropriately to the anxiety levels of the human while not undermining the importance of its own safety and work performance. The reduced architecture is shown in Figure 1.

A seen in Figure 1, in the top-left "robot input" quadrant, Oracle receives information from both the world and the human through various sensors. The world information is obtained through the infrared sensors, touch sensors, light sensors etc. Oracle receives this information, infers the world state and forms a model of the world for itself. This is an instantaneous snapshot of the world that assists Oracle during navigating. The human related information is obtained through biofeedback sensors that provide physiological signals of the human, for instance- cardiac activity, electrodermal activity, muscle activity,

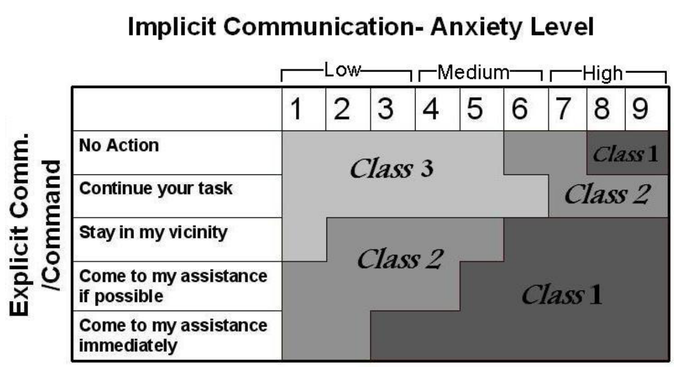

Figure 2. Generating Triggers from Implicit and Explicit Communication

temperature etc. This information is used to interpret the affective state (emotional state) of the human, for example to judge whether the human is getting stressed, fatigued, or inattentive (implicit communication). Oracle also receives explicit commands from the human through the control sensors (via PC keyboard). The human's intention is combined with his/her level of anxiety employing context based reasoning to predict the urgency of the situation. Three triggers indicating the urgency level of the situation (Class 1, Class 2 and Class 3) are generated depending upon the implicit and explicit communication from the human. The details are shown in Figure 2. For instance if Oracle implicitly senses that the human is showing a high level of anxiety and his/her explicit command is "Come to my assistance now", Oracle interprets this as a high urgency level situation and classifies it as a Class 1 trigger. On the other hand if the anxiety level of the human is low and he/she explicitly commands Oracle to continue it own task of exploration then Oracle interprets this as low urgency level situation and assigns Class 3 trigger to it.

The "robot output" quadrant contains nodes that determine the behavior of Oracle. Oracle uses its representation of the world, knowledge of its own goals and the urgency level of the situation to determine the best course of action. Oracle is assisted by a 6-tier subsumption model [61] as shown in Figure 3 to determine the priorities of the tasks. Class 1, Class 2 and Class 3 behaviors are activated by the respective triggers shown in Figure 2. A behavior on top subsumes or suppresses the behavior below it. Hence, Class 1 behavior has the highest priority and exploration has the lowest priority. Oracle's decision results either in an action or initiation of speech on its part. In the "human input" quadrant (Figure 1) the human receives information both from the world and Oracle. The human can perceive the dialogues initiated by Oracle and observe its behavior. He/she then exploits this knowledge to infer Oracle's state as well as predict what it might do next. Such inference along with the world representation that the human forms and his/her own ultimate goals is employed by the human to determine the next action. The resulting human's action might be simply to monitor Oracle's actions or issue a command to it. Depending on the situation, the human might also decide to not do anything. Hence, in each cycle of the loop, there is methodical information flow in between the world, Oracle and the human. At the very fundamental level, this is a *sense-infer-plan-act* loop wherein, Oracle and the human utilize the available information to interact with each other and to take actions that influence each other and the world. Oracle uses pre-recorded speech while the human uses keyboard to communicate with each other.

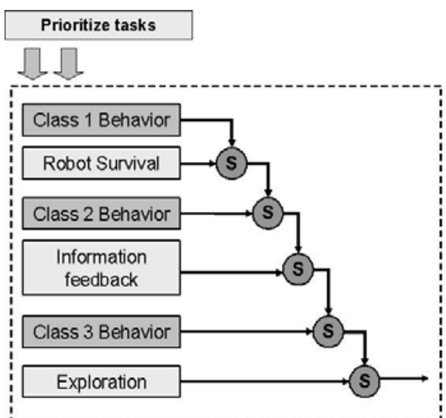

Figure 3. 6-Tier Subsumption Architecture

In the last paper [6] we presented a hybrid subsumption model to determine Oracle's behavior. The architecture presented in Figure 1 has been developed further on the hybrid subsumption model so that it explicitly includes the input and output to the human in the loop and also accounts for the human reasoning behind the action that he/she takes. In this architecture, Oracle combines implicit and explicit communication from the human in order to be able to predict the urgency level of the situation. This makes the system more robust as the false triggers can be eliminated and the missed triggers can be identified. There is also a tighter coupling between the human and Oracle through an interface that enables Oracle to query the human and provide suggestions (via speech) from time to time. The human sends his/her responses to Oracle though a keyboard input that is wirelessly transmitted to the robot.

5. Experiment

5.1 *Task description*

The objective of the experiment was to develop and implement real-time, emotion-sensitive human-robot co-ordination that would enable the robot to recognize and respond to the psychological states of a human.

In this experiment we simulated a human and Oracle working in close coordination on an exploration task. An ideal real life situation analogous to this may be an astronaut and a robotic vehicle exploring a planet, each carrying out the exploration task independently with the robot being responsive to the astronaut's affective states (for instance stress, panic or fatigue).

The experiment consisted of two major components: first, designing an adaptive neuro-fuzzy inference base emotion-recognizer that could identify or "understand" the physiological responses of a person and second, implementing a human-robot co-operation task consisting of Oracle navigating a workspace and an operator/user whose physiological state was being continuously monitored. At any

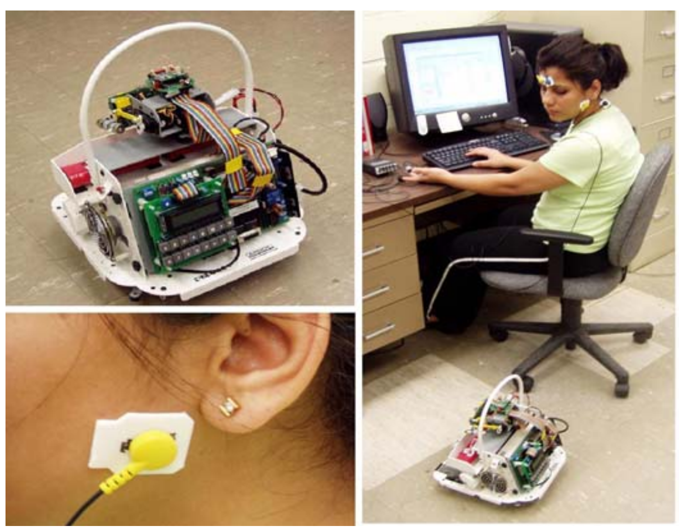

Figure 4. (Clockwise from top left) (i) Oracle- the mobile robot that served as a test-bed, (ii) An operator wearing sensors communicating wirelessly with Oracle, (iii) Close-up of the biofeedback sensors worn by the operator.

given time Oracle's sensors provided it with information regarding the world state and the operator state. The infrared range finder and the touch gave information regarding the obstacles in the workspace, the compass indicated the orientation of Oracle, the optical encoders indicated the motor speed and distance traveled by Oracle and the biofeedback sensors gave an indication of the emotional state of the human.

To obtain pilot data, human subjects were presented with cognitive computer tasks that elicited anxiety. During the tasks, the subject's physiology was monitored with the help of wearable biofeedback sensors (Figure 4) and Procomp+ data acquisition system [50]. The Procomp+ sensors are small and comfortable to wear without interfering with a person's normal activities. The digitally sampled sensor information was sent serially to the computer using a fiber optic cable. This sensor data indicating physiological response of the subject was used to train the fuzzy inference system.

The second part of the experiment consisted of implementing a real-time human-robot interaction framework that would enable Oracle to recognize the human's psychological state through continuous physiological sensing, and act accordingly to address the psychological needs of the human. Oracle- a mobile robot [62] was used in the implementation of the human-robot co-ordination task (Figure 4). Oracle's tasks included:

(i) Exploring the workspace
(ii) Avoiding obstacles in the workspace
(iii) Wall following
(iv) Providing environment related information to the human.
(v) Responding to the urgency of the situation in the following manner
    a) Class I Trigger - Raise an alarm, send warning signal to the computer, reach the human in shortest possible time
    b) Class II Trigger – Move to the vicinity of the operator
    c) Class III Trigger- Initiate speech to query the operator or give suggestions

The priorities of the execution of the above tasks were decided by a 6-tier subsumption model, which has been discussed in detail in the Section 4. This experiment consisted of an exploration task in which Oracle was expected to navigate a given workspace using some basic behaviors like obstacle avoidance and wall following. Oracle also received implicit input (physiological signals) and explicit input (keyboard input) from the human working with it. Oracle combined the explicit and implicit input to determine its behavior and modified its actions accordingly.

5.2. *Results*

5.2.1 *Neuro-adaptive fuzzy inference system*

Figure 5 and Figure 6 show the original membership functions that were used for inference and the modified membership functions that were obtained by using the neuro-adaptive training method for two input features- mean transit time and mean level of phasic activity of skin conductance. In Figure 5, the top tier (a) shows the three membership functions (MFs) that were initially designed to fuzzify the input. The lower tier (b) of the same figure shows the MFs after they were modified by adaptive neuro-fuzzy learning techniques. We can observe that adaptive neuro fuzzy training of the MFs, tunes the shape of the MFs in Figure 6 also.

The classification error decreased significantly on using the neuro-adaptive fuzzy inference system to predict the probable anxiety level based on the physiological features. Figure 7 shows the improved performance of adaptive neuro-fuzzy inference over normal fuzzy inference. For all the subjects there was a significant reduction in the mean percentage error of classification.

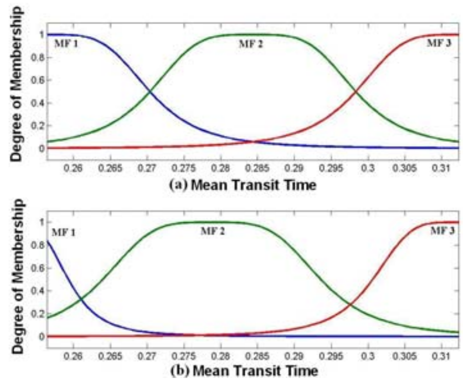

Figure 5. (a) Original Fuzzy Inference MFs (b) Adaptive Neuro-fuzzy Inference MFs for Mean Transit Time

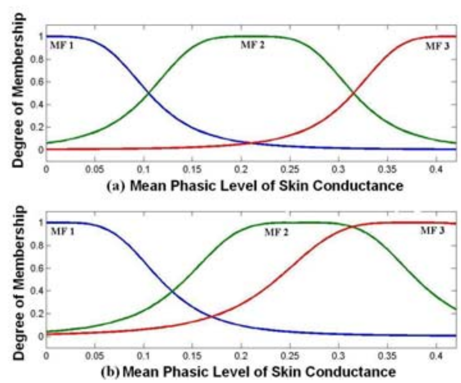

Figure 6(a) Original Fuzzy Inference MFs (b) Adaptive Neuro-fuzzy Inference Mfs for Mean Phasic Activity

The error was calculated as shown in eq. 1.

$$\text{Mean \% Error} = \frac{1}{n}\sum_{i=1}^{n}\frac{|actual - predicted| * 100}{predicted} \qquad \text{eq. 1}$$

Where actual = actual level of anxiety, predicted = predicted level of anxiety, n = total number of data points

The error reduced by 18% for Subject 1, 14% for Subject 2, 8% for Subject 3, and 9% for Subject 4. The anxiety level of a subject could be detected approximately with a success rate of 88% using the adaptive neuro-fuzzy techniques.

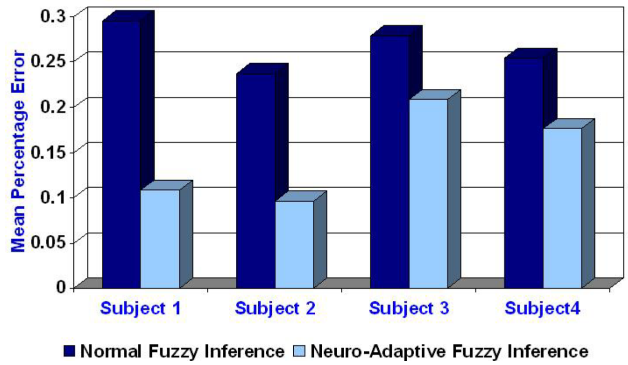

Figure 7. Comparison of the Mean Percentage Error

5.2.2 *Experimental demonstration of adaptive robot behavior*

Figure 8 and Figure 10 demonstrate the capability of Oracle -the emotion-sensitive robot to change its behavior based on the interpretation of the urgency of the situation. Oracle combines the information regarding the human's anxiety level obtained through the implicit communication channel with the information regarding the human's intent obtained through the explicit communication channel to determine the urgency level of the situation. Figure 2 in Section 4 shows the matrix that is utilized to interpret the implicit and explicit communication in order to evaluate the situation. Figure 8 and Figure 10 show Oracle and the human in the lab setting where the experiments were carried out. The human operator and Oracle embarked on an exploration task in which Oracle moved around the workspace, avoiding obstacles and following the wall, while the operator remained stationed at his desk. Figure 8 shows the path taken by Oracle in absence of any implicit communication from the human. Oracle in this case performed the given task of exploring the workspace and giving relevant feedback regarding the environment to the human from time to time. The operator remained at his desk performing his own tasks exclusive of the Oracle's behavior.

Figure 10 shows Oracle's performance when the implicit communication channel is active. In this case Oracle is sensitive to the emotions of the human operator and uses its own interpretation regarding the operator's emotions to determine the urgency level of the situation. The operator's needs can be deduced from the level of urgency of the situation. Apart from the urgency of the situation, other factors that Oracle considers while planning its next move are the state of the world and Oracle's own goals. Oracle utilizes a six- layer subsumption model to find out the priority of the various tasks that need to be fulfilled at any given time.

Since it was not feasible to stress a human subject every time we ran an experiment, the physiological signals were recorded during a separate experiment. Part of this physiological data (training data) was used to train the adaptive neuro-fuzzy based anxiety detecting system. The remaining data (testing data) was used in the human-robot experiment to demonstrate Oracle's adaptive behavior.

The testing data was transmitted unaltered to Oracle at the time of the experiment as if it were coming from the operator in real-time.

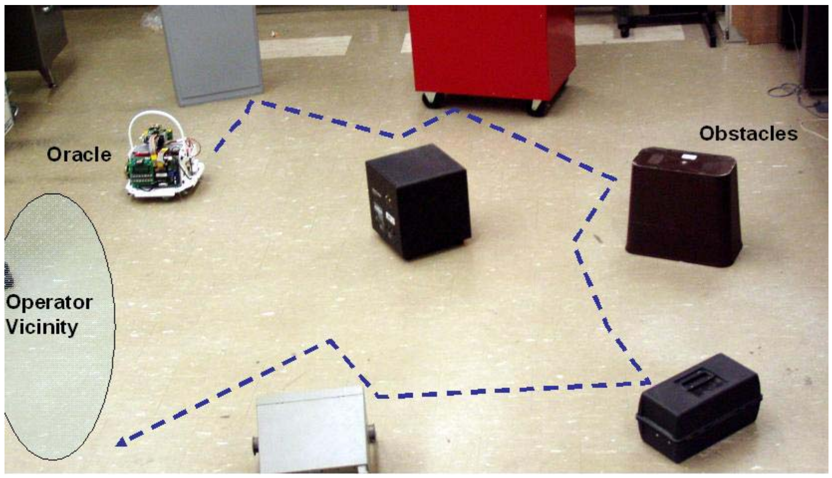

Figure 8. Path taken by Oracle in absence of implicit communication

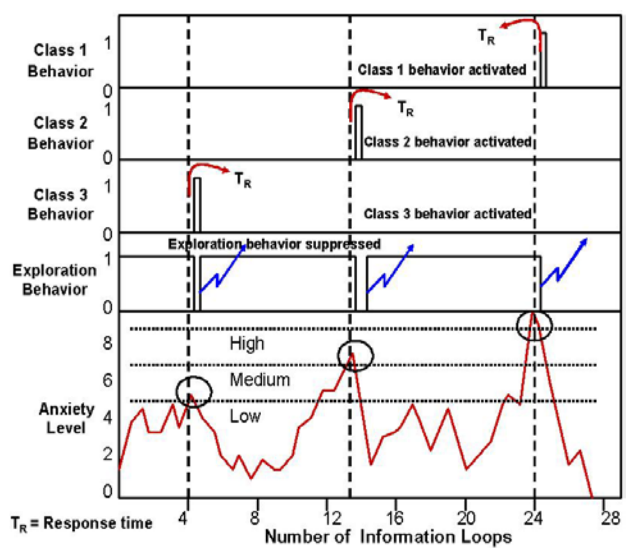

Figure 9. Behavior adaptation by Oracle

Figure 9 shows the variation of the anxiety level of the operator during the task. As mentioned in Section 5, there were three thresholds that were established to classify the anxiety of the operator- low, medium and high anxiety threshold. The session that is shown in Figure 9 was chosen because the subject displayed a gradually increasing level of anxiety over time. Three triggers were generated during the course of the session – Class 1, Class 2, and Class 3 trigger. Figure 10 shows the points in Oracle's path when these triggers are encountered. Each time Oracle encounters these triggers, its behavior changes to accommodate the human's needs. As seen in Figure 9, a Class 3 trigger is generated when the anxiety level crosses the "low" threshold. This activates Class 3 behavior in which Oracle suspends its exploration and initiates a speech informing the operator that the task may be causing him/her to get stressed and that it (Oracle) will be available for help. Oracle then continues its exploration task till a Class 2 trigger is received. Oracle subsumes it wandering behavior and moves to the vicinity of the human (shown as dark shaded area in Figures 8 and 10) using light tracking (only the operator area is brightly lit) so that it can be of immediate assistance when required. Once within the vicinity Oracle carries out its explorations tasks. It can be observed that Class 2 trigger indicates a higher level of urgency than Class 1 trigger. Finally when Oracle gets Class 1 trigger it immediately reaches the operator and offers assistance. The activation and deactivation of various behaviors can be seen in Figure 9. Here, it should be noted that in order to prevent chattering in Oracle's behavior, an "incubation period" of 10 seconds was defined. Whenever, the anxiety level of the operator crossed the low or the medium threshold, Oracle waited for the incubation period before triggering any behavior. If during the incubation period it was observed that the anxiety level stabilized or started to decrease, Oracle would trigger the behavior corresponding to the last threshold crossed. However, if the anxiety level showed an increasing trend, then Oracle would not trigger a series of alternating behaviors. It would wait till the highest threshold was crossed or the current level stabilized or started to decrease. This phenomenon can be observed in Figure 9.

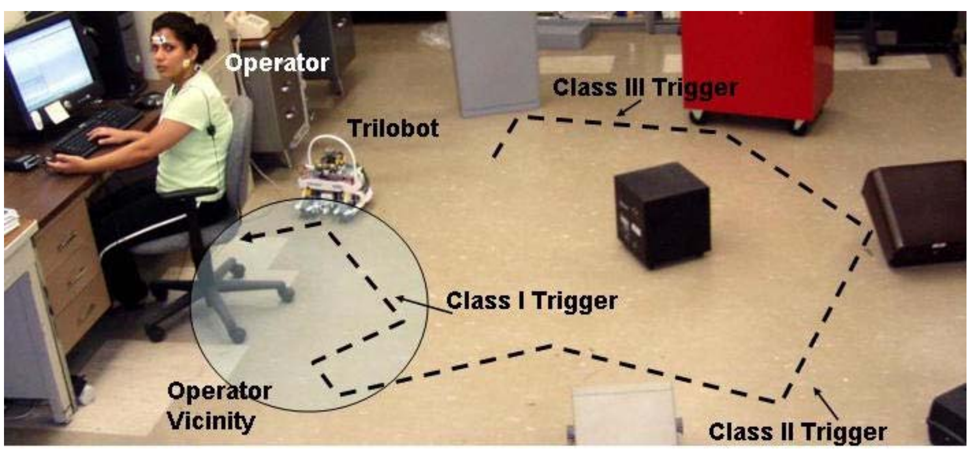

Figure 10. Path taken by Oracle in presence of implicit communication

6. Conclusions

We proposed an innovative human-robot interaction structure wherein the robot was sensitive to the emotions of the human it worked with and could adapt its behavior to address the anxiety shown by the human. This approach synergistically combined concepts in affective computing, psychology, and robotics to develop a robotic system capable of combining implicit and explicit channels of communication from the human to intelligently determine its optimal behavior. Adaptive neuro-fuzzy inference system yielded reliable emotion recognition results and the level of anxiety was detected with approximately 88% success. We have experimentally demonstrated that the robot can adapt its behavior based on the emotional state of the human.

Future work would consist of expanding the range of tasks and contexts to which this framework can be applied and increasing the reliability and sophistication of emotion recognition. We would also like to work towards increasing the range of emotions detected and discriminated beyond anxiety to include frustration, fatigue, boredom, etc.

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