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12

A New Approach to Implicit Human-Robot Interaction Using Affective Cues

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Abstract – It is well known that in social interactions, implicit communication between the communicators plays a significant role. It would be immensely useful to have a robotic system that is capable of such implicit communication with the operator and can modify its behavior if required. This paper presents a framework for human-robot interaction in which the operator's physiological signals were analyzed to infer his/her probable anxiety level and robot behavior was adapted as a function of the operator affective state. Peripheral physiological signals were measured through wearable biofeedback sensors and a control architecture inspired by Riley's original information-flow model was developed to implement such human-robot interaction. The target affective state chosen in this work was anxiety. The results from affect-elicitation tasks for human participants showed that it is possible to detect anxiety through physiological sensing in real-time. A robotic experiment was also conducted to demonstrate that the presented control architecture allowed the robot to adapt its behavior based on operator anxiety level.
Keywords: human-robot interaction, implicit communication, physiological sensing, affective computing, anxiety

1. Introduction

There has been a steady progress in the field of intelligent and interactive robotics over the last two decades ushering in a new era of personal and service robots. The World Robotics 2005 survey [1] reports that over 1,000,000 household robots were in use, a number that is anticipated to exceed several million in the next few years. As robots and people begin to co-exist and cooperatively share a variety of tasks, "natural" human-robot interaction that resembles human-human interaction is becoming increasingly important.

Reeves and Nass [1] have already shown that people's interactions with computers, TV and similar machines/media are fundamentally social and natural, just like interactions in real life. Human interactions are characterized by explicit as well as implicit channels of communication. While the explicit channel transmits overt messages, the implicit one transmits hidden messages about the communicator (his/her intention, attitude and like/dislike). Ensuring sensitivity to the other party's emotions or sensibility is one of the key tasks associated with the second, implicit channel [3]. Picard in [5] states that "emotions play an essential role in rational decision-making, perception, learning, and a variety of other cognitive functions". Therefore, endowing robots with a degree of emotional intelligence should permit more meaningful and natural human-robot interaction.

The potential applications of robots that can detect a person's affective states and interact with him/her based on such perception are varied and numerous. Whether it is the domain

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of personal home aids that assist in cleaning and transportation, toy robots that engage and entertain kids, professional service robots that act as assistants in offices, hospitals, and museums, or the search, rescue and surveillance robots that accompany soldiers and firefighters – this novel aspect of human-robot interaction will impact them all.

For a robot to be emotionally intelligent it should clearly have a two-fold capability-the ability to display its own emotions and the ability to understand human emotions and motivations (also called referred to as affective states). The focus of our work is to address the later capability, i.e., to endow a robot with the ability to recognize human affective states. There are several works that focus on making robot display emotions just like human beings – usually by using facial expressions and speech. Some prominent examples of such robots are -Pong robot developed by the IBM group [6], Kismet and Leonardo developed in MIT [6], and ATR's (Japan) Robovie-IIS [8]. Our work is complementary to this research. Fong et al. in their survey [9] provide details of many existing socially interactive robots that have been developed as personal robots, entertainment toys, therapy assistants and to serve as test beds to validate social development theories.

There are several modalities such as facial expression, vocal intonation, gestures, postures, and physiology that can be utilized to determine the underlying emotion of a person interacting with the robot. A rich literature exists in computer vision for automatic facial expression recognition [10]. However, integration of such system with robots to permit real-time human emotion recognition and robot reaction have been very few. Bartlett et al. have developed a real-time facial recognition system that has been deployed on robots such as Aibo and Robovie [11]. Gestures and postures recognition for human-robot interaction is a relatively new area of research, which includes vision-based interfaces to instruct mobile robots via arm gestures [12]. Most of these approaches, however, recognize only static pose gestures. The interpretation of user emotions from gestures is a much more involved task and such work in the context of human-robot interaction is not known. On the other hand, vocal intonation is probably the most understood and valid area of nonverbal communication. Vocal intonation or the tone of our voice can effectively measure the affective (emotional) content of speech. The effects of emotion in speech tend to alter the pitch, timing, voice quality, and articulation of the speech signal [13] and reliable acoustic features can be extracted from speech that vary with the speaker's affective state [6].

Physiology is yet another effective and promising way of estimating the emotional state of a person. In psychophysiology (the branch of psychology that is concerned with the physiological bases of psychological processes), it is known that emotions and physiology (biological signals such as heart activity, muscle tension, blood pressure, skin conductance etc.) are closely intertwined and one influences the other. Research in affective computing, pioneered by Picard exploits this relationship between emotions and physiology to detect human affective states [14]. While concepts from psychophysiology are now being enthusiastically applied to human-computer interaction [15] and other domains such as driving [16], flying [17], and machine operation [18], the application of this technique in robotics domain is relatively new [19]. Our preliminary work in [20] presented concepts and initial experiment for a natural and intuitive human-robot interaction framework based on detection of human affective states from physiological signals by a robot.

The paper is organized as follows: Section II presents the scope and rationale of the paper. Section III describes our proposed theoretical framework for detecting affective cues in human-robot interaction. This section provides the details of the physiological indices used for anxiety detection, use of regression tree for prediction of anxiety and the control

architecture for human-robot interaction. The experimental design details are presented in Section IV along with the results and discussion. Finally, Section V summarizes the contributions of the paper and provides important conclusions.

2. Scope and Rationale of the Paper

This paper develops an experimental framework for holistic (explicit and implicit) human–robot interaction by synergistically combining emerging theories and results from robotics, affective computing, psychology, and control theory. The idea is to build an intelligent and versatile robot that is affect-sensitive and capable of addressing human's affective needs. *This paper focuses on human affect recognition by a robot based on peripheral physiological signals of the human obtained from wearable biofeedback sensors*. While the proposed framework can be utilized to detect a variety of human affective states, in this paper we focus on detecting and recognizing anxiety.

Anxiety was chosen as the relevant affective state to focus on for two primary reasons. First, anxiety plays an important role in various human-machine interaction tasks that can be related to task performance. Hence, detection and recognition of anxiety is expected to improve the understanding between humans and machines. Second, the correlation of anxiety with physiology is well established in psychophysiology literature [21] and thus provides us with an opportunity to detect it by psychophysiological analysis.

Affective states have potentially observable effects over a wide range of response systems, including facial expressions, vocal intonation, gestures, and physiological responses (such as cardiovascular activity, electrodermal responses, muscle tension, respiratory rate etc.) [5]. However, in our work we have chosen to determine a person's underlying affective state through the use of physiological signals for various reasons. An attempt to examine all available types of observable information would be immensely complex, both theoretically and computationally. Also, physical expressions (facial expressions, vocal intonation) are culture, gender, and age dependent thus complicating their analysis. On the other hand physiological signals are usually involuntary and tend to represent objective data points. Thus, when juxtaposed with the self reports, physiological measures give a relatively unbiased indication of the affective state. Moreover, they offer an avenue for recognizing affect that may be less obvious to humans but more suitable for computers. Another important reason for choosing physiology stems from our aim to detect affective states of people engaged in real-life activities, such as working on their computers, controlling a robot, or operating a machine. In most of these cases, even if a person does not overtly express his/her emotion through speech, gestures or facial expression, a change in the physiology pattern is inevitable and detectable. Besides, there exists evidence that the physiological activity associated with various affective states is differentiated and systematically organized. There is a rich history in the Human Factors and Psychophysiology literature of understanding occupational stress [22], operator workload [23], mental effort [24] and other similar measurements based on physiological measures such as electromyogram (EMG), electroencephalogram (EEG), and heart rate variability (HRV). In another work, multiple psychophysiological measures such as HRV, EEG, and blink rates among others were employed to assess pilots' workload [24]. Heart period variability (HPV) has been shown to be an important parameter for mental workload relevant to human-computer interaction (HCI) [26]. Wilhelm and colleagues have also worked extensively on various physiological signals to assess stress, phobia, depression and other social and clinical problems [27].

3. Theoretical Framework for Human-Robot Interaction Based on Affective Communication

A. Physiological indices for detecting anxiety

The physiological signals that were initially examined in our work along with the features derived from each signal are described in Table 1. These signals were selected because they can be measured non-invasively and are relatively resistant to movement artifacts. Additionally, measures of electrodermal activity, cardiovascular activity, and EMG activity of the chosen muscles have been shown to be strong indicators of anxiety [28][29]. In general, it is expected that these indicators can be correlated with anxiety such that higher physiological activity levels can be associated with greater anxiety [30].

Multiple features (as shown in Table 1) were derived for each physiological measure. "Sym" is the power associated with the sympathetic nervous system activity of the heart (in the frequency band 0.04-0.15 Hz.). "Para" is the power associated with the heart's parasympathetic nervous system activity (in the frequency band 0.15-0.4 Hz.). InterBeat Interval (IBI) is the time interval in milliseconds between two "R" waves in the ECG waveform in millisecond. IBI ECGmean and IBI ECGstd are the mean and standard deviation of the IBI. Photoplethysmograph signal (PPG) measures changes in the volume of blood in the finger tip associated with the pulse cycle, and it provides an index of the relative constriction versus dilation of the blood vessels in the periphery. Pulse transit time (PTT) is the time it takes for the pulse pressure wave to travel from the heart to the periphery, and it is estimated by computing the time between systole at the heart (as indicated by the R-wave of the ECG) and the peak of the pulse wave reaching the peripheral site where PPG is being measured. Heart Sound signal measures sounds generated during each heartbeat. These sounds are produced by blood turbulence primarily due to the closing of the valves within the heart. The features extracted from the heart sound signal consisted of the mean and standard deviation of the 3rd, 4th, and 5th level coefficients of the Daubechies wavelet transform. Bioelectrical impedance analysis (BIA) measures the impedance or opposition to the flow of an electric current through the body fluids contained mainly in the lean and fat tissue. A common variable in recent psychophysiology research, pre-ejection period (PEP) derived from impedance cardiogram (ICG) and ECG measures the latency between the onset of electromechanical systole, and the onset of left-ventricular ejection and is most heavily influenced by sympathetic innervation of the heart [31]. Electrodermal activity consists of two main components – Tonic response and Phasic response. Tonic skin conductance refers to the ongoing or the baseline level of skin conductance in the absence of any particular discrete environmental events. Phasic skin conductance refers to the event related changes that occur, caused by a momentary increase in skin conductance (resembling a peak). The EMG signal from Corrugator Supercilii muscle (eyebrow) captures a person's frown and detects the tension in that region. It is also a valuable source of blink information and helps us determine the blink rate. The EMG signal from the Zygomaticus Major muscle captures the muscle movements while smiling. Upper Trapezius muscle activity measures the tension in the shoulders, one of the most common sites in the body for developing stress. The useful features derived from EMG activity were: mean, slope, standard deviation, mean frequency and median frequency. Blink movement could be detected from the Corrugator Supercilii activity.

Physiological Response	Features derived	Label used	Unit of measurement
Cardiac activity	Sympathetic power	Sym	Unit/Square Second
	Parasympathetic power	Para	Unit/Square Second
	Ratio of Sympathetic to Parasympathetic power	Sym Para	Unit/Square Second
	Mean IBI	IBI ECG_{mean}	Milliseconds
	Std. of IBI	IBI ECG_{std}	Standard Deviation (no unit)
	Mean amplitude of the peak values of the PPG signal (Photoplethysmogram)	PPG $Peak_{mean}$	Micro Volts
	Standard deviation (Std.) of the peak values of the PPG signal	PPG $Peak_{std}$	Standard Deviation (no unit)
	Mean Pulse Transit Time	PTT_{mean}	Milliseconds
Heart Sound	Mean of the 3^{rd},4^{th}, and 5^{th} level coefficients of the Daubechies wavelet transform of heart sound signal	Mean d3 Mean d4 Mean d5	No unit
	Standard deviation of the 3^{rd},4^{th}, and 5^{th} level coefficients of the Daubechies wavelet transform of heart sound signal	Std d3 Std d4 Std d5	No unit
Bioimpedance	Mean Pre-Ejection Period	PEP_{mean}	Milliseconds
	Mean IBI	IBI ICG_{mean}	Milliseconds
Electrodermal activity	Mean tonic activity level	$Tonic_{mean}$	Micro-Siemens
	Slope of tonic activity	$Tonic_{slope}$	Micro-Siemens/Second
	Mean amplitude of skin conductance response (phasic activity)	$Phasic_{mean}$	Micro-Siemens
	Maximum amplitude of skin conductance response (phasic activity)	$Phasic_{max}$	Micro-Siemens
	Rate of phasic activity	$Phasic_{rate}$	Response peaks/Second
Electromyographic activity	Mean of Corrugator Supercilii activity	Cor_{mean}	Micro Volts
	Std. of Corrugator Supercilii activity	Cor_{std}	Standard Deviation (no unit)
	Slope. of Corrugator Supercilii activity	Cor_{slope}	Micro Volts/Second
	Mean Interbeat Interval of blink activity	IBI $Blink_{mean}$	Milliseconds
	Mean amplitude of blink activity	Amp $Blink_{mean}$	Micro Volts
	Standard deviation of blink activity	$Blink_{std}$	Standard Deviation (no unit)
	Mean of Zygomaticus Major activity	Zyg_{mean}	Micro Volts
	Std. of Zygomaticus Major activity	Zyg_{std}	Standard Deviation (no unit)
	Slope. of Zygomaticus Major activity	Zyg_{slope}	Micro Volts/Second
	Mean of Upper Trapezius activity	$Trap_{mean}$	Micro Volts
	Std. of Upper Trapezius activity	$Trap_{std}$	Standard Deviation (no unit)
	Slope. of Upper Trapezius activity	$Trap_{slope}$	Micro Volts/Second
	Mean and Median frequency of Corrugator, Zygomaticus and Trapezius	$Zfreq_{mean}$ $Cfreq_{median}$ $Tfreq_{mean}$ etc.	Hertz
Temperature	Mean temperature	$Temp_{mean}$	Degree Centigrade
	Slope of temperature	$Temp_{slope}$	Degree Centigrade/Second

Table 1. Physiological Indices.

Mean amplitude of blink activity and mean interblink interval were also calculated from Corrugator EMG. The various features extracted from the physiological signals were combined in a multivariate manner and fed into the affect recognizer as described in the next section. Some of these physiological signals, either in combination or individually, have previously been used by

others to detect a person's affective states when deliberately expressing a given emotion or engaged in cognitive tasks [14]. Our approach was to detect anxiety level of humans while they were engaged in cognitive tasks on the computer and embed this sensing capability in a robot. To our knowledge, till date no work has investigated real-time modification of robot behavior based on operator anxiety in a biofeedback-based human-robot interaction framework. Various methods of extracting physiological features exist but efforts to identify the exact markers related to emotions, such as anger, fear, or sadness have not been successful chiefly due to person-stereotypy and situation-stereotypy [29]. 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). The novelty of the presented affect-recognition system is that it is both individual-and context-specific in order to accommodate the differences encountered in emotion expression. It is expected that in the future with enough data and understanding, affect recognizers for a class of people can be developed.

B. Anxiety Prediction based on Regression Tree

In the previous research works in emotion recognition, change in emotion has been considered either along a continuous dimension (e.g., valence or arousal) or among discrete states. Various machine learning and pattern recognition methods have been applied for determining the underlying affective state from cues such as facial expressions, vocal intonations, and physiology. Fuzzy logic has been employed for emotion recognition from facial expression [33]. Fuzzy logic has also been used to detect anxiety from physiological signals by our research group [19] and by Hudlicka et al. in [17]. There are several works on emotion detection from speech based on k-nearest neighbors algorithm [34], linear and nonlinear regression analysis [35]. Discriminant analysis has also been used to detect discrete emotional states from physiological measures [36]. A combination of Sequential Floating Forward Search and Fisher Projection methods was presented in [35] to analyze affective psychological states. Neural networks have been extensively used in detecting facial expression [37], facial expression and voice quality [38]. The Bayesian approach to emotion detection is another important analysis tool that has been used successfully. In [39] a Bayesian classification method was employed to predict the frustration level of computer users based on pressure signals from mouse sensors. A Naïve Bayes classifier was used to predict emotions based on facial expressions [40]. A Hidden Markov Model based emotion detection technique was investigated for emotion recognition [41].

In this paper we have used regression trees (also known as decision trees) to determine a person's affective state from a set of features derived from physiological signals. The choice of regression tree method emerges from our previous comparative study of four machine learning methods-K -Nearest Neighbor, Regression Tree, Bayesian Network and Support Vector Machine as applied to the domain of affect recognition [42]. The results showed that regression tree technique gave the second best classification accuracy – 83.5% (after Support Vector Machines that showed 85.8% accuracy) and was most space and time efficient. Regression tree method has not been employed before for physiology-based affect detection and recognition.

Regression tree learning, a frequently used inductive inference method, approximates discrete valued functions that adapt well to noisy data and are capable of learning disjunctive expressions. For the regression tree-based affect recognizer that we built, the input consisted of the physiological feature set and the target function consisted of the affect levels (participant's self-reports that represented the participant's assessment of his/her own affective state). The main challenge was the complex nature of the input physiological data sets. This complexity was primarily due to the (i) high dimensionality of the input feature space (there are currently forty

six features and this will increase as the number of affect detection modalities increases.), (ii) mixture of data types, and (iii) nonstandard data structures. Additionally, a few physiological data sets were noisy where the biofeedback sensors had picked up some movement artifacts. These data sets had to be discarded, resulting in the missing attributes.

The steps involved in building a regression tree are shown in Figure 2. Physiological signals recorded from the participant engaged in PC-based task were processed to extract the input feature set. The participant's self-report at the end of each epoch regarding his/her affective states provided the target variable or the output. While creating the tree, two primary issues were: (i) Choosing the best attribute to split the examples at each stage, and (ii) Avoiding data over fitting. Many different criteria could be defined for selecting the best split at each node. In this work, Gini Index function was used to evaluate the goodness of all the possible split points along all the attributes. For a dataset D consisting of n records, each belonging to one of the m classes, the Gini Index can be defined as:

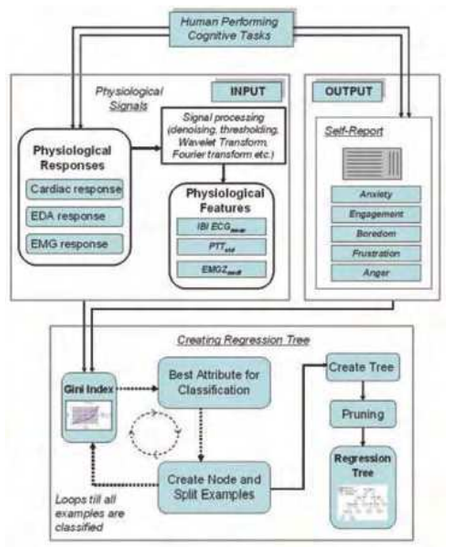


Fig. 1. Creating Regression Tree.

$$Gini(D) = 1 - \sum_{i=1}^{n} p_i^2 \qquad \text{eq. 1}$$

where pi is the relative frequency of class i in *D*. If *D* is partitioned into two subsets *D1* and *D2* based on a particular useful attribute, the index of the partitioned data *Gini(D,C)* can be obtained by:

$$Gini(D,C) = \frac{n_1}{n} Gini(D_1) + \frac{n_2}{n} Gini(D_2) \qquad \text{eq. 2}$$

where *n1* and *n2* are the number of examples of *D1* and *D2*, respectively, and *C* is the splitting criterion. Here the attribute with the minimum *Gini Index* was chosen as the best attribute to split. Trees were pruned based on an optimal pruning scheme that first pruned branches that gave the least improvement in error cost. Pruning was performed to remove the redundant nodes as bigger, overfitted trees have higher misclassification rates. Thus,

based on the input set of physiological features described earlier, the affect recognizer provided a quantitative understanding of the person's affective states.

C. Control Architecture

As emphasized in Section 1, for a peer level human-robot interaction to mimic similar human-human interaction, it is essential that the robot has implicit communication in addition to explicit exchange of information with the human. While explicit communication allows the human and the robot to exchange information regarding the goals, task to be performed, the current task being executed and other such issues, implicit communication makes it possible for the robot to detect the emotional states of the human, and take necessary steps to assist the human by addressing his/her emotional need. There is currently no such controller that enables a robot to be responsive to an implicit channel of communication from the operator while it (the robot) performs its routine tasks.

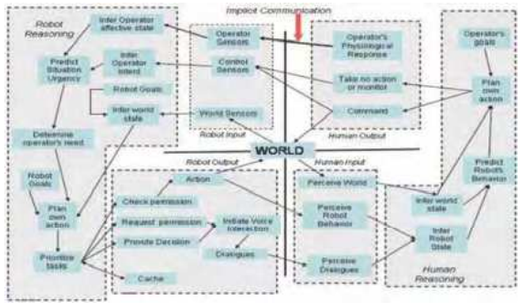


Fig. 2. Control Architecture.

A generalized model of human-machine system developed by Riley [43] represents an information flow that can be systematically modified according to any rule-base to represent a particular level of automation in human-machine interaction. This general model represents the most complex level of automation embedded in the most complicated form of human-machine interaction. However, this model does not provide any means for implicit communication. We altered Riley's model to develop our framework that contains a distinct information channel for implicit affective communication. This new framework (as shown in Figure 1) is able to accommodate most human-robot cooperative tasks. In order to keep our presentation of the control architecture tractable, we focused on a typical exploration setting in this paper where a human and a mobile robot (Oracle) worked together in an unknown environment to explore a given region. In this case, the Oracle was expected to behave as an intelligent partner to the human. This required Oracle to respond appropriately to the emotional states (i.e., anxiety levels, in this case) of the human while not undermining the importance of its own safety and work performance. The details of this task can be found in the next section.

4. Experimental Investigation

A. Experimental Design – Scope and Limitations

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 varying levels of user anxiety. In this experiment we simulated a scenario where a human and a robot needed to work in close coordination on an exploration task. The experiment consisted of the following major components: 1) design and development of tasks that could elicit the targeted

affective states from the human subjects; 2) system development for real-time physiological data acquisition; 3) development and implementation of an affect recognition system based on regression tree technique; 4) design and implementation of a robot control architecture that was responsive to human anxiety; and 5) design and implementation of a task prioritization technique for Oracle that allowed it to modify its behaviors.

The experiment to demonstrate implicit communication between a human and a robot where the robot could change its behavior to address human affective need was performed in two stages: first, physiological signals were recorded from the participants while they were involved in carefully designed cognitive tasks (described later) that elicited the target affective states; and second, streaming the collected physiological data continuously to the Oracle as if it were coming in real-time from the operator. This two-stage arrangement was done due to the following practical difficulties:

1. Eliciting high anxiety in a human-robot interaction task is risky and requires fail-safe design. One needs to demonstrate the feasibility of affect-sensitive robot behavior in an open-loop manner before one can get IRB permission for closed-loop experiments.
2. Eliciting anxiety, frustration and other affective states through computer tasks is less resource consuming. Doing the same with mobile robots would require longer hours of training to run the robots. We would also need to provide safe operating conditions to avoid accidents, larger work area and more equipment to accommodate robot damage than available to us.
3. Psychologists have already designed cognitive tasks that have been shown to elicit anxiety with high probability. However, there is no similar work on robot task design that, with a high probability, will generate anxiety. Especially in a laboratory environment it is extremely difficult to design such a task because of resource limitations. Since our objective was to be able to detect anxiety when it occurs, we employ cognitive tasks without compromising our research objectives.

The two-part experiment described above is expected to serve as a proof-of-concept experiment demonstrating the use of physiological feedback to infer the underlying affective states, which is then used to adapt robot behavior. However, it is expected that in the future, better availability of resources and better task design would enable us to perform field experiments with professional robot operators. These experiments would be closed-loop, where both the physiological state of the operator working with a robot will be monitored in real-time and the operator responses to change in robot behaviors will be evaluated. However, before such steps can be taken, open-loop experiments will be useful to verify the proposed concepts.

Task Design: To obtain physiological data, human subjects were presented with two cognitive computer tasks that elicited various affective states. The two tasks consisted of an anagram solving task, and a Pong playing task. The anagram solving task has been previously employed to explore relationships between both electrodermal and cardiovascular activity with mental anxiety. Emotional responses were manipulated in this task by presenting the participant with anagrams of varying difficulty levels, as established through pilot work. The Pong task consisted of a series of trials each lasting up to four minutes, in which the participant played a variant of the early, classic video game "Pong". This game has been also used in the past by researchers to study anxiety, performance, and gender differences. Various parameters of the game were manipulated to elicit the required affective responses. These included: ball speed and size, paddle speed and size, sluggish or over-responsive keyboard and random keyboard response.

During the tasks, the participants periodically reported their perceived subjective emotional states. This information was collected using a battery of five self-report questions rated on a

nine-point Likert scale. Self-reports were used as reference points to link the objective physiological data to participants' subjective affective state. Each task sequence was subdivided into a series of discrete epochs that were bounded by the self-reported affective state assessments. These assessments occurred every three minutes for the anagram task and every 2-4 minutes for the Pong task. The participants reported their affective state on a scale of 0-9 where 0 indicated the lowest level and 9 indicated the maximum level.

During the experiment, physiological signals (shown in Table1) were continuously collected during each task. A pair of biofeedback sensors was placed on the distal phalanges of the non-dominant hand's index and ring fingers to detect the electrodermal activity. Skin temperature was monitored from a sensor placed on the distal phalange of the same hand's small finger; and the relative pulse volume was monitored by a photoplethysmograph placed in the distal phalange of that hand's middle finger. The ECG was monitored using a two-sensor placement on the participants' chest. The EMG was monitored using bipolar placements of miniature sensors over the left eyebrow (Corrugator Supercilli), the cheek muscle (Zygomaticus Major) and the shoulder muscle (Upper Trapezius). Bioimpedance was recorded through spot electrodes placed symmetrically on both sides of the neck and thorax region.

The sensors and data collection system were wearable. The sensors were small, light weight, non-invasive, and FDA approved. As a result, the experimental set-up permitted the participants to move with minimal restriction. However, they were not completely free to walk around because of the needed ethernet communication with the computer. This restriction did not impede task performance since the tasks were presented at the computer terminal. Our objective was to demonstrate the feasibility of affect detection and recognition using wearable sensors. Once the scientific objective is achieved and the advantages demonstrated, miniaturization of the sensors and providing wireless connections would be investigated as future work.

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 [45] was used in the implementation of the human-robot coordination task. It is a popularly used test bed for behavior-based robotics experiments. We provided the high-level controller and software needed to command Oracle to do complicated tasks. Controlling the Oracle was done by sending low-level commands from a desktop PC using a standard RS-232 serial port. There are several options for controlling Oracle including using a desktop PC with a tether cable or a radio datalink. In this experiment commands were wirelessly sent to Oracle via a radio datalink that allowed control over the drive motors, heading motion, gripper, sensors, etc. All the software development was done in Matlab environment.

Physiological data acquisition: Physiological signals (shown in Table1) were continuously collected during each task in the first experiment. A pair of biofeedback sensors was placed on the distal phalanges of the non-dominant hand's index and ring fingers to detect the electrodermal activity. Skin temperature was monitored from a sensor placed on the distal phalange of the same hand's small finger; and the relative pulse volume was monitored by a photoplethysmograph placed in the distal phalange of that hand's middle finger. The ECG was monitored using a two-sensor placement on the participants' chest. The EMG was monitored using bipolar placements of miniature sensors over the left eyebrow (Corrugator Supercilli), the cheek muscle (Zygomaticus Major) and the shoulder muscle (Upper Trapezius). Bioimpedance was recorded through spot electrodes placed symmetrically on both sides of the neck and thorax region. The sensors were small, light weight, non-invasive, and FDA approved. As a result, the experimental set-up permitted the participants to move with minimal restriction. However, they were not completely

free to walk around because of the needed ethernet communication with the computer and sensor connections to the amplifiers and transducers. This restriction did not impede task performance since the tasks were presented at the computer terminal. Our objective was to demonstrate the feasibility of affect detection and recognition using wearable sensors. Once the scientific objective is achieved and the advantages demonstrated, miniaturization of the sensors and providing wireless connections would be investigated as future work.

Affect recognition system based on regression tree: When the human-robot exploration task started, physiological data collected in the first part of the experiment was sent to the robot as if coming from the operator in real time. This physiological data was processed to extract relevant features from the signals. A regression tree-based affect recognizer (created earlier) was utilized to determine operator's level of anxiety based on these features. The affect-recognizer accepted as input physiological features and produced as output the probable anxiety level of the operator as a scalar in the range 0-9 (where 0 indicated almost no anxiety and 9 indicated very high anxiety level).

Design and implementation of control architecture: Mixed-initiative based control architecture was employed to implement affect-sensitive human-robot interaction. The modified control architecture is shown in Figure 1. As seen from the figure, in the top-left "robot input" quadrant, Oracle received information from both the world and the human through various sensors. The world information was obtained through the infrared sensors, touch sensors, light sensors etc. Oracle received this information and inferred the world state. The human-related information was obtained through biofeedback sensors that provided physiological signals. This information was used to interpret the affective (emotional) state of the human, for example to judge whether the human is getting stressed, fatigued, or inattentive (implicit communication). Oracle also received explicit commands from the human through the control sensors (explicit communication). The human's intention was combined with his/her emotional state employing context based reasoning to predict the type of the situation. Three triggers indicating the type of the situation (Class 1, Class 2 and Class 3) were generated depending upon the implicit and explicit communication from the human. The details are shown in Figure 4. For instance, if Oracle implicitly sensed that the human was showing a high level of anxiety and his/her explicit command was "Come to my assistance immediately", Oracle interpreted this as a high priority level situation and classified it as a Class 1 trigger. On the other hand, if the anxiety level of the human was low and he/she explicitly commanded Oracle to continue its own task of exploration then Oracle interpreted this as a low priority situation and assigned Class 3 trigger to it.

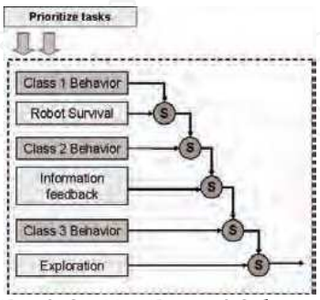


Fig. 3. Six-Tier Figure 2 Subsumption Model.

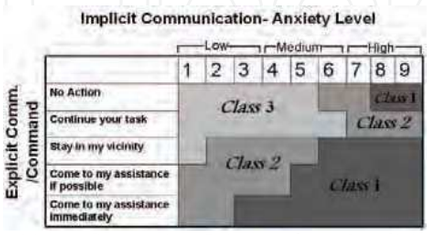


Fig. 4. Generating Triggers from Implicit and Explicit Communication.

The "robot output" quadrant contained nodes that determine the behavior of Oracle. Oracle used 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 was assisted by a Six-tier subsumption model as shown in Figure 3 to determine the priorities of the tasks. Class 1, Class 2 and Class 3 behaviors associated with the respective triggers. More details on these behaviors are given in the following paragraph. A behavior on top subsumed or suppressed the behavior below it. Hence, Class 1 behavior had the highest priority and exploration had the lowest priority. Oracle's decision resulted either in physical motion or initiation of speech by Oracle. As seen from the "human input" quadrant, the human received information from the world as well as Oracle. The human could perceive the dialogues initiated by Oracle and observe its behavior. He/she then exploited 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 formed and his/her own ultimate goals was employed by the human to determine the next action. The resulting human's action could be to simply monitor Oracle's actions or issue a command to it. Depending on the situation, the human could also decide to not do anything. Hence, in each cycle of the loop, there was a methodical information flow among the world, Oracle and the human. At the very fundamental level, this is a sense-infer-plan-act loop involving both explicit and implicit information wherein, Oracle and the human utilized the available information to interact with each other and to take actions that influenced each other and the world. Task prioritization technique for Oracle: The behavior modifications of Oracle depended upon the level of operator anxiety that was detected. Oracle's basic 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: ·
    Class I Trigger -Raise an alarm, Send warning signal to the computer, reach the human in shortest possible time
    Class II Trigger – Move to the vicinity of the operator
    Class III Trigger-Initiate a dialogue with the operator to inquire 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 previously. At any given time Oracle's sensors provided it with information regarding the world state and the operator state. The infrared range finder and the touch sensors 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.

B. Results

Results of the two-part experiment described above are given in the following sections. Affect Recognition: Fifteen data sets were collected (one for each participant.) Each data set contained six hours of physiological signal recording. This was in addition to the ten minutes of baseline (or reference) data on each day. Each participant completed approximately 100 task epochs. These sessions spanned the anagram and Pong tasks. Wearable sensors were used to continuously monitor the person's physiological activities, and the physiological features as mentioned in Section III(A) were calculated using customized algorithms. The self-reports of the participants indicated the affective state of the person at various times while performing the tasks.

There were significant correlations observed between the physiology of the participants and their self-reported anxiety levels. This was in accordance with the claim of psychophysiologists that there is a distinct relationship between physiology and affective states of a person. It was also observed that the physiological activity associated with each affective state was distinct and the transition from one affective state to another was accompanied by dynamic shifts in physiological activities. Due to the phenomena of person stereotypy no two participants had exactly the same set of useful (highly correlated) features. Figure 5 shows the physiological features that were highly correlated with the state of anxiety for participant 5 and the corresponding correlation of the same features with the state of anxiety for participant 11. An absolute
correlation greater than equal to 0.3 was considered significant. It can be seen from Figure 5 that two features – mean of pulse transit time (PTTmean) and mean of temperature (Temp mean) are correlated differently for the two participants. While both were correlated positively with anxiety for participant 11, they were negatively correlated for participant 5. However, features like mean interbeat interval of impedance (IBI ICGmean), sympathetic activity power (Sym) and mean frequency of EMG activity from zygomaticus major (Zfreqmean) were similarly related for both participants. However, since our approach to affect detection and recognition was person-specific, such expected differences among participants did not create problems.

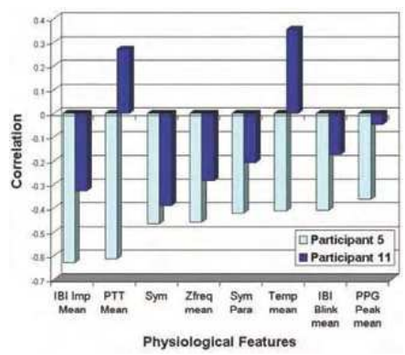


Fig. 5. Person Stereotypy for the affective state of anxiety.

In spite of differences across participants, there were some features that were more useful than the others across all the participants. It was seen that mean of pre-ejection period (PEPmean) was a useful feature for nine out of fifteen participants when detecting anxiety. Similarly mean interbeat interval derived from ECG (IBI ECGmean) was another important feature that was well correlated with anxiety for seven participants.
It was also observed that each affective state for any participant had a unique set of feature correlates– that is the set of features correlated with anxiety were distinct from those correlated with boredom or engagement. Since the signature of each affective state was different, it was expected that a distinction between anxiety and boredom/engagement/anger/frustration could be made based on the physiological features alone. Figure 6 shows the average percentage accuracy in distinction between anxiety and other states across the fifteen participants. These values were calculated using the method of confusion matrix. It can be seen that on the basis of physiology alone, a state of anxiety could be distinguished from a state of anger 82% of the times, from state of frustration 76% of the times and from states of engagement and boredom 85% and 86% of the times respectively.

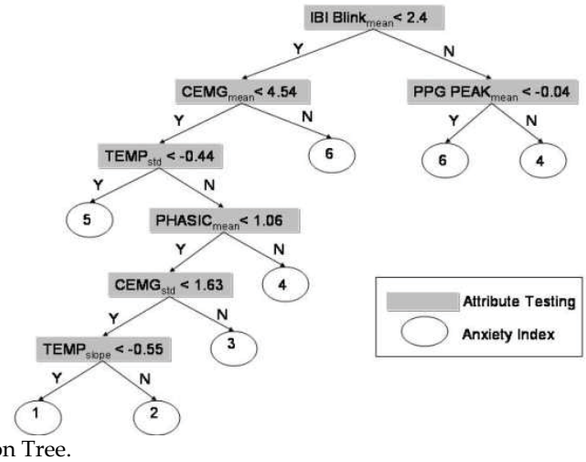


Fig. 6. Regression Tree.

As mentioned in Section III(B), regression tree methodology was employed to detect affective state from physiological features. One of the regression trees generated is shown in Figure 7. As can be seen, the attribute that was found most useful for splitting the data was the mean interbeat interval of the blink activity (IBI Blinkmean). If the IBI Blinkmean was more than 2.4, the next attribute used for splitting was mean amplitude of the PPG peak (PPG Peakmean). If this values was less than -0.04, then the predicted anxiety index was six else it was four. Similar splitting was performed along the other branches of the regression tree. The numerical values seen are obtained after baselining the actual values using the following equation:

$$AV_B = \frac{AV_R - AV_C}{AV_R} \qquad \text{eq. 3}$$

Where AVB is the attribute value after baselining, AVR is the attribute value during the baseline period (or the reference value), and AVC is the attribute value during the current period.

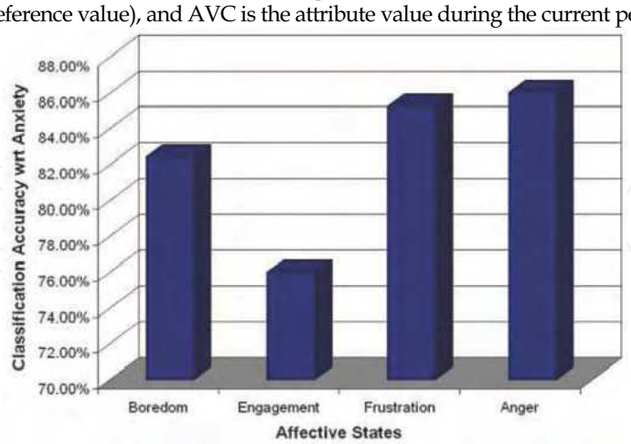


Fig. 7. Classification accuracy of anxiety with regard to other affective states.

Human-Robot Exploration task: The 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 her desk. Oracle's task was that of exploring the workspace and giving relevant feedback regarding the environment to the human from time to time. The operator remained at her desk performing her own tasks exclusive of the Oracle's behavior. Oracle was sensitive to the anxiety level of the human operator and used its own interpretation to determine the nature of the situation. Other factors that Oracle considered while planning its next move were the state of the world and its own goals. It utilized the six-layer subsumption model described earlier to find out the priority of the various tasks that needed 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 session. These signals were transmitted unaltered to Oracle at the time of the experiment in the same manner as if they were being recorded in real-time. Ten sessions were conducted during which physiological data from ten of the fifteen participants was used. The five participants whose data was not used did not show sufficient variation in their anxiety. Figure 8(a) shows the rate of false alarms (when high anxiety was detected falsely) and missed alarms (when high anxiety was misclassified as low). The average rate of false alarms was 10.55 % while the rate of missed alarm was 12.48 % across the ten participants. The average rate of accuracy as seen from Figure 8(b) was 76.97 %.

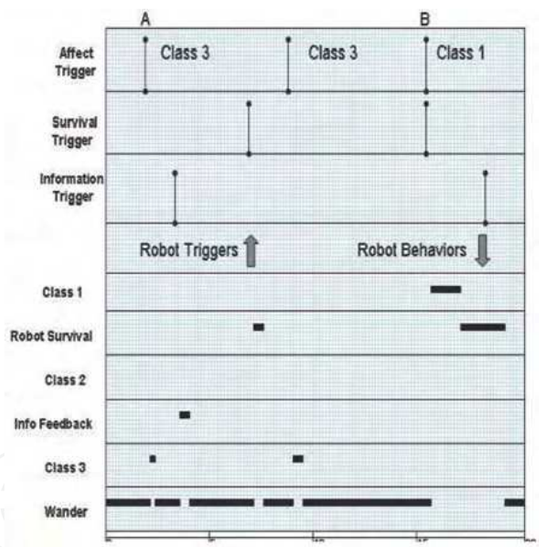


Fig. 8. Behavior Adaptation by oracle.

Figure 9 demonstrate the capability of Oracle -the emotion-sensitive robot to adapt its behavior based on the affective state of the operator. In this figure a 20 minute task session has been presented during which the different behaviors of Oracle based on the various triggers are shown. 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 whether it is a Class I, II or III trigger.

Figure 4 in Section III shows the matrix that is utilized to interpret the implicit and explicit communication in order to evaluate the situation. Figure 9 shows how the behavior of Oracle changes according the various triggers that it generates or receives from the operator. It can be seen that a Class 3 trigger is generated while Oracle is in the wander behavior (Point A). This activates Class 3 behavior in which Oracle suspends its exploration and initiates a speech-based dialogue informing the operator that it (Oracle) will be available for help. Oracle then continues its exploration task till an information feedback trigger is received from the operator polling Oracle for certain task details. Oracle subsumes it wandering behavior and switches to the information feedback behavior. It can be observed that Oracle remains in the wandering behavior most of the times and switches amidst the other behaviors as and when the relevant triggers are activated. It can be seen that in the second half of the task, Class I trigger and survival trigger are received at the same time (Point B). Class I trigger having the higher priority induces the Oracle to move from wandering behavior to Class I behavior. The Oracle raises an alarm and then processes the survival trigger which was previously sent to the cache.

C. Contributions and Discussion

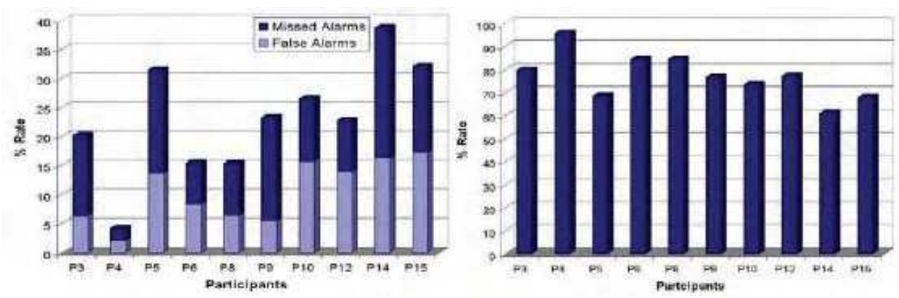


Fig. 9. (a) Average rate of false and missed alarms, and (b) Average rate of accuracy in anxiety prediction.

The main contributions of this work as demonstrated by the above experimental results are: 1) Physiological signals are a powerful indicator of underlying affective states and can play an important role in implicit communication between a human and a robot. 2) There exist both person stereotypy and context stereotypy. Our method of emotion recognition is both person specific and context specific to overcome these problems. And 3) A robot control architecture can be designed that can integrate both explicit and implicit communication between a human and a robot. In this specific experiment we have demonstrated that a robot that works with a person can detect the anxiety of the person and can act on it appropriately. These actions will depend on need of the situation and the capability of the robot. Anxiety was chosen to be the target affective state in this work because it plays an important role in various human-machine interaction tasks that can be related to task performance. Detection and recognition of anxiety is expected to improve the understanding between humans and robots. However, this framework is not limited to detecting anxiety alone and can be used for other affective states as well. Our objective here was to demonstrate that such a framework could be realized. It is, to our knowledge, one of the first works in the field of human-robot interaction where the robot could be made sensitive to human anxiety. Specific set of robot actions will be functions of specific missions and are beyond the scope of this work.

Related works in the area of affective computing have been summarized in Section I. Most works focus on methods for recognizing a person's discrete emotional states while deliberately expressing pure emotions such as joy, grief, anger, etc. A mong the other works that detect affective states of people engaged in real-life tasks, most use overt signals such as facial expressions, voice or speech. Even those that use physiology have not used context-and person-specific techniques for learning physiological patterns. Also, there is no known human-robot interaction framework functional in this context that uses such a comprehensive set of physiological features for real-time emotion detection and robot behavior adaptation. In this work we detect the anxiety level purely on the basis of physiological signals. The objective of the presented work is to detect and isolate anxiety along a continuous axis. We collected physiological data from participants engaged in real cognitive computer-based tasks. The indices derived from these biological signals were used for recognition of affective states.

Currently the presented human-robot interaction based on affective communication framework has been verified in open-loop experiments. The rationale for conducting open-loop experiments have been explained in Section IV. We are planning to conduct closed-loop experiments in the future. However, that will not be possible in our laboratory environment because of space and resource limitations. We are currently seeking collaboration for field experiments where professional robot operators can participate in the study.

5. Conclusion and Future Work

An approach to human-robot interaction that can utilize implicit affective communication along with explicit communication is presented. In this work we focus on the state of anxiety as the target affective state. A set of physiological indices have been presented that showed good correlation with anxiety. The affect recognition technique infers the underlying affective state of the human from peripheral physiological signals using regression theoretic methodology. A control architecture is presented that can integrate the affective information with the operator's explicit information to achieve a versatile and natural human-robot interaction.

An experiment was conducted where human-robot communication was enhanced by enabling the robot to sense human anxiety. In order to perform this experiment two separate cognitive tasks were designed to elicit anxiety. 15 human subjects took part in this study where each participant involved in the cognitive tasks for 6 hours. Since it was not possible to create anxiety while working with the robot within laboratory environment because of both resource limitations and safety issues, these data from the cognitive tasks were used in real-time for the human-robot experiment. The experiment demonstrated that if such data is available, i.e., if a human experiences anxiety while working with a robot, the robot could detect and interact with the human in real-time. Thus the experiment demonstrated for the first time to our knowledge that human-robot interaction can be performed where affective cues can play an important role. Future work will involve in performing closed-loop experiments as well as detecting other affective states.

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