Robotica (2004) volume 22, pp. 85–95. © 2004 Cambridge University Press
DOI: 10.1017/S0263574703005319 Printed in the United Kingdom

Anxiety detecting robotic system – towards implicit human-robot collaboration

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(Received in Final Form: May 3, 2003)

SUMMARY

A novel affect-sensitive human-robot cooperative framework is presented in this paper. Peripheral physiological indices are measured through wearable biofeedback sensors to detect the affective state of the human. Affect recognition is performed through both quantitative and qualitative analyses. A subsumption control architecture sensitive to the affective state of the human is proposed for a mobile robot. Human-robot cooperation experiments are performed where the robot senses the affective state of the human and responds appropriately. The results presented here validate the proposed framework and demonstrate a new way of achieving implicit communication between a human and a robot.

KEYWORDS: Anxiety detection; Human-robot framework; Affect recognition; Control architecture.

1. INTRODUCTION

The main focus of this paper is on human-robot coordination based on implicit communication from human to robot. Implicit communication, in the context of this paper, is defined primarily as affective communication[1] where the affective state of the person is *interpreted* by the robot. We include implicit states such as frustration, anxiety, engagement and fatigue within the domain of affective states. Such a capability, alone or in conjunction with other capabilities that allow explicit instructions from a human, is expected to provide a new paradigm for human-robot (and human-computer) interaction that will be intuitive, smooth and efficient.[1] It was clearly shown in reference [2] that even rudimentary implicit communication significantly improved the performance of human-computer interaction. The capability of the robot to alter its autonomy level (or in some cases, task priority) based on human interaction is another hallmark of a successful human-centered robotic system.[3] Consider several human-robot exploration scenarios in space, underwater, Antarctica, inside a dormant volcano and in other similar risky environments where a human can often encounter dangerous situations. Upon encountering such a danger, the human's reaction is likely to be one of panic, fear, or anxiety. A robot that is capable of sensing these internal psychological states can immediately take meaningful actions to help the person. A similar situation may arise in human-robot search and rescue operations or in fire fighting. Robotic aid for rehabilitation could also use affect sensing capability to provide exercise sequences that are comfortable for the person. A robot that could sense the fatigue of the worker on the shop floor with whom it works would be able to take necessary precautions to avoid accidents. All these potential applications will eventually lead to the development of personal robots that will act as understanding companions of humans.

Figure 1 presents affect-sensitive human-robot coordination architecture as developed in this paper. The physiological signals from a human engaged in some task are recorded. These signals are processed to determine the affective state of the human. The affective state information along with other environmental inputs is used by a controller to decide the next course of action. The controller instructs the robot to perform the desired action. The human who is working in cooperation with the robot is then influenced by the robot's action, and the cycle begins anew.

In this paper we focus on using physiological measurements to sense the person's affective state. Physiological responses are generally involuntary and less dependent on culture, gender and age than are other indicators of emotion, such as facial expressions or voice. Physiology offers an avenue for recognizing affect that may be less obvious for humans but more suitable for robots and computers, which can quickly implement signal processing and pattern recognition tools to infer underlying affective states. Recent

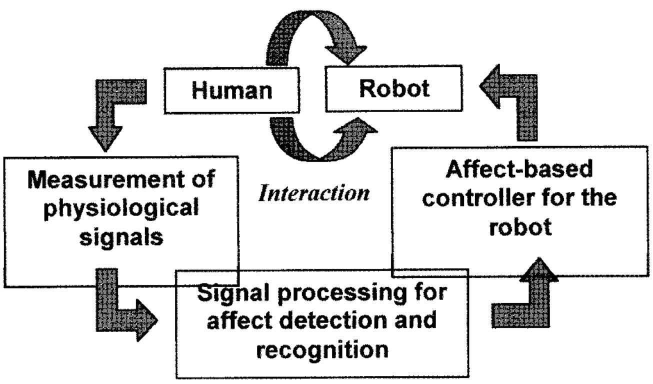

Fig. 1. Human-robot interaction framework.

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advances in *wearable computers* and *affective computing*[4] have ushered in the era of small and lightweight biofeedback sensors that can sense and process physiological signals in a non-invasive manner that are comfortable for the user to wear, unobtrusive, and fast enough for real-time applications.[5] Such capabilities inspire us to use physiological sensing as an initial means to recognize human affect for our proposed controller. The potential of physiological sensing for affect recognition has already been demonstrated by the pioneering work of Dr. Picard and her colleagues.[6,7] In our earlier paper,[8] we presented our initial effort in stress detection using wearable sensing technology.

We have, however, added a new dimension to the research on affective computing by expanding and integrating it with a robotic system that can use this information and respond to the affective need shown by its human companion. We have developed a robot control architecture that uses the psychological state information to formulate and execute an action plan. This action plan may require that the robot change its autonomy level or adjust task priorities within the same autonomy level.

2. PHYSIOLOGICAL INDICES FOR AFFECT RECOGNITION

There is good evidence that the physiological activity associated with affective state is differentiated and systematically organized. The transition from one affective state to another, for instance from a relaxed to an anxious mental state, is accompanied by dynamic shifts in physiological activities. The physiological signals we will initially examine include: various parameters of cardiovascular activity,[9,10] including interbeat interval and relative pulse volume, electrodermal activity (tonic and phasic skin conductance activity[11–15]) and facial electromyographic (EMG) activity (including activity of the corrugator supercilii [eyebrow] and masseter [jaw] muscles.[16,17] These signals have been selected because they can be measured non-invasively and are relatively resistant to movement artifact.

By combining these multiple indicators of emotion in a multivariate manner, we will be able to provide the affect recognizers we will be developing with a rich array of information from which to infer the person's affective state. Many of these signals, either in combination or separately, have been used to detect affective states of a person who is *deliberately* expressing a given emotion while at rest. In our paper we have adopted the more challenging task of identifying the person's affective state online while the person is actively engaged in a task and then designing a robot controller that is sensitive to human affect.

3. AFFECT DETECTION

In this paper we have used the physiological responses of a person to detect that person's level of anxiety. We briefly describe the steps of analyzing the physiological responses discussed in Section 2.

We examined a broad range of parameters derived from the physiological responses. The ones that are focused upon in the following part are those that proved to be most useful for anxiety detection in the current experiment. The main physiological responses that we have used to determine the anxiety level of a particular individual are: Cardiac response (ECG signal, blood volume pulse signal), Electrodermal response, and Electromyographic response.

3.1 Cardiac Response

Raw ECG signal: Time domain measures are the simplest way of evaluating heart rate variability (HRV). HRV has immense potential to determine the role of autonomic nervous system (ANS) fluctuations in the human body. The ANS controls smooth muscle, gland activity and cardiac muscle. It is this system of the body and its control over cardiac function that is of interest for anxiety detection. The ANS is divided into two branches – the sympathetic nervous system branch (SNS) (with dominant function in emergency or so-called "fight or flight" situations) and the parasympathetic branch (PNS) (associated with more vegetative functions such as digestion, relaxation, sexual activity, etc.). Increased activity of the sympathetic branch causes an increase in the heart rate while an increase in the parasympathetic branch results in a slowing down of the heart rate. Under normal situations there is a balance between these two systems placing the body in a state of homeostasis. However under a state of mental stress this balance will be altered.[8,10,18–21] Heart Rate Variability can be used to detect this change in system balance.

Using Biofeedback sensors raw ECG of the human subject performing a task is recorded. The sampling rate of the encoder used is 1000 Hz. A typical ECG waveform is shown in Figure 2. Each R-wave in the figure corresponds to the point of *systole*, the point in the heartbeat where the heart reaches maximal contraction to pump the blood through the body. The number of beats in a minute is called the *heart rate* and is typically 70-80 beats per minute at rest.

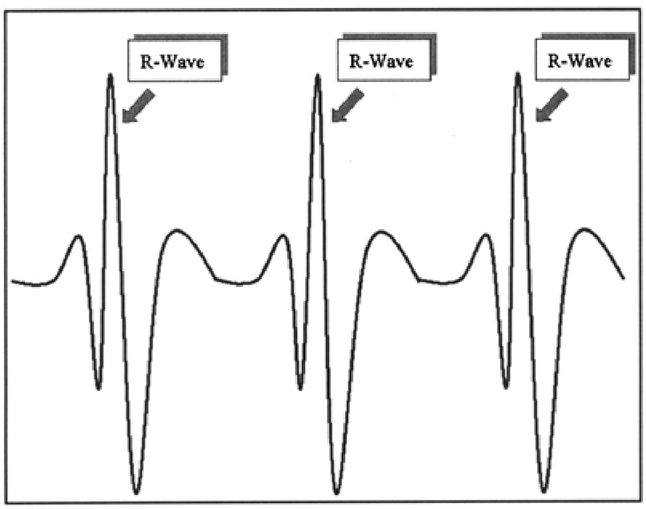

Fig. 2. A typical ECG waveform showing the R-waves.

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(a) **InterBeat Interval (IBI).** The time in millisecond between two normal "R" waves (Fig. 2) is called the Inter Beat Interval (IBI). IBI is a valuable index for measuring heart rate variability. IBI variability can be determined either in the *time domain* or in the *frequency domain*. Time domain analysis has the limitation of needing very large sets of data (~24 hrs) for accurate analysis. Frequency analysis does not have this shortcoming and allows the use of much smaller data sets. Since we are interested in measuring anxiety during a task, we prefer frequency domain analysis to time domain analysis. From the raw ECG signal a time series of IBIs is extracted using a peak detection algorithm.

(b) **Power spectral analysis.** A power spectral analysis is performed on the IBI data to localize the sympathetic and parasympathetic frequency ranges. Parasympathetic and sympathetic nervous system activity have been associated with two frequency bands. The high frequency (HF) component (0.15–0.4 Hz; which corresponds to the rate of normal respiration) measures the influence of the vagus nerve in modulating the sinoatrial node and is associated with parasympathetic nervous system activity. The low frequency (LF) component (0.04–0.15 Hz.) provides an index of sympathetic effects on the heart. These associations between frequency bands and nervous system activity have been made through the use of functional and pharmacological testing.[20,21] When a human being is anxious, it is commonly observed that the parasympathetic activity of his/her heart decreases and the sympathetic activity increases. We have exploited this feature of heart rate variability to detect anxiety in a human subject.

(c) **Wavelet packet analysis.** Power in the exact frequency range is calculated using wavelet analysis.[22–24] In the Wavelet Packet (WP) decomposition,[25,26] the approximation coefficients as well as the detail coefficients are recursively decomposed using the same filtering and down sampling techniques that are used in Discrete Wavelet Transform. Figure 3 show the tree decomposition used for wavelet packet analysis. A wavelet packet analysis provides us with a convenient tool to analyze a signal for a desired frequency without losing the time information. The wavelet packets can be used for numerous expansions of a given signal, from which we can extract the exact frequency band that we are interested in. The WP decomposition of the input signal is performed by computing the convolution of the signal $f[n]$ with the wavelet atoms:

$$w[n]=2^{-j/2}\sum_{k} f[n]W_p(2^{-j/2}k-n) \qquad (2)$$

These wavelet atoms can be obtained from the high pass filter ($g[n]$) and the low pass filter ($h[n]$)

$$W_{2p}(t)=\sqrt{2}\sum_{n} h[n]W_p(2t-n) \qquad (3)$$

$$W_{2p+1}(t)=\sqrt{2}\sum_{n} g[n]W_p(2t-n) \qquad (4)$$

Each atom W_p $(2^{-j/2}k-n)$ is characterized by three parameters – frequency p, scale j, and position m. For our purpose, we have used the Daubechies wavelet filter db5. This filter has been used because it best extracts the frequency contents that are required to analyze the IBI signal. The wavelet db5 has been used for ECG signal processing in many cases.[27,28] The parameters obtained: sympathetic power (S_p) and parasympathetic power (P_p).

3.2 Electrodermal Activity. Raw Skin Conductance Activity (SCA)

Skin Conductance Activity – one of the several kinds of EDA, describes changes in the skin's ability to conduct electricity, which occur due to interaction between environmental events and an individual's psychophysiological state.[13,15] One of the fastest responding measures of anxiety/stress response, it has been found to be one of the most robust and non-invasive physiological measures of sympathetic activity. The SCA signal was sampled at 1000 Hz. A typical signal has been shown in Figure 4. We denoised the raw SCA signal and then decomposed it into its tonic and phasic components. Then we measured the mean amplitude of phasic responses and the rate at which these occurred.

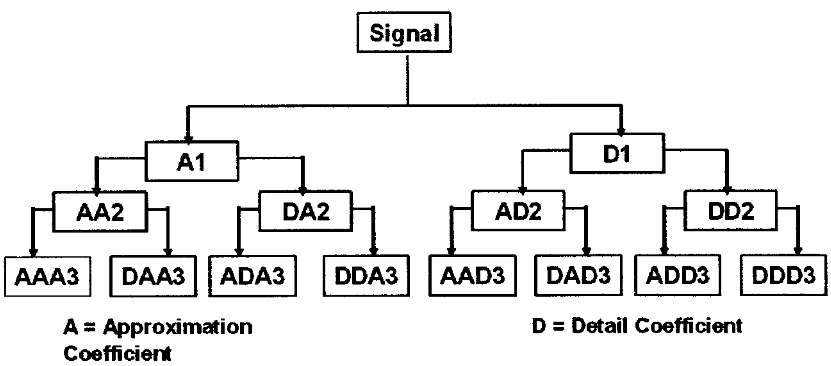

Fig. 3. Wavelet packet decomposition.

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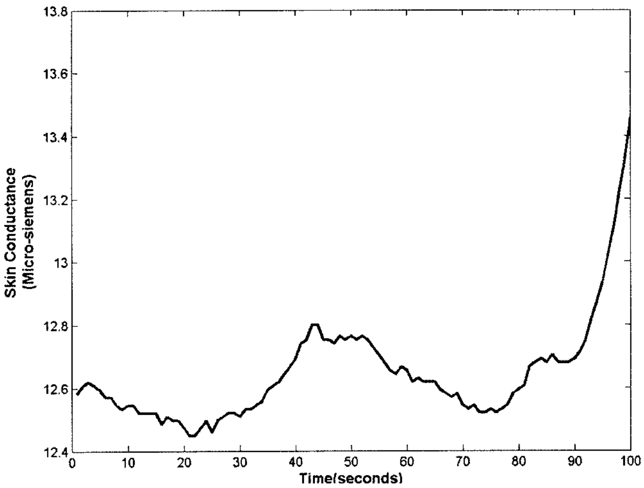

Fig. 4. A typical skin conductance signal.

Phasic response measures the event-related responses that occur in an individual. Occurrences of environmental stimuli cause time-related changes in the skin conductance. A stimulus may be anything from a thought burst to a deep sigh. A skin conductance response (SCR) caused by a momentary increase in skin conductance, resembles a peak. The characteristics of a typical SCR are shown in Figure 5.

We had the following criterion for considering a particular peak as a valid skin conductance response:

(i) The slope of the rise to the peak should be greater than 0.05 Micro-Siemens/minute
(ii) The amplitude should be greater than 0.05 Micro-Siemens
(iii) The rise time should be greater than 0.25 sec.

Using a response detection algorithm, we count the number of such responses that meet the above criterion in a given interval and determine the rate of response for the given task (number of responses per minute). The mean phasic amplitude is also computed which is simply the mean of the amplitudes of all the responses in a given epoch. All the signal points that are not included in the response constitute the tonic part of the skin conductance signal. The parameters obtained: mean phasic amplitude (P_m) and rate of phasic response (P_r).

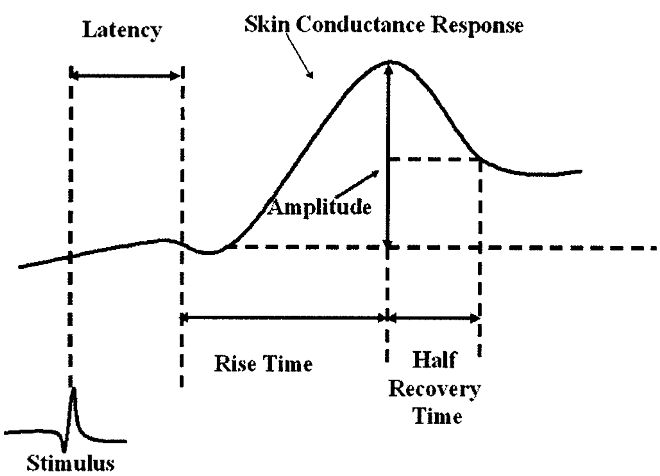

Fig. 5. A skin conductance response.

3.3 *Electromyographic Activity*

The electromyogram (EMG) sensor placed over a particular muscle measures the electrical activity associated with that particular muscle's contraction or movement.[16,17] Electromyographic activity over the eyebrow region (of the corrugator supercilii muscle) and the jaw region (of the masseter muscle) has been studied extensively because anxiety, tension or mental efforts are often accompanied by increased EMG activity over these sites. Activities like frowning, jaw-clenching, etc. have a high correlation with the affective state of a person and are reflected in increased EMG activity. A typical EMG signal (rectified and integrated) is shown in Figure 6. The signal was sampled at 1000 Hz. It is rectified and integrated within the encoder system before digitization.

(a) **Corrugator Activity.** The EMG signal from the corrugator supercilii muscle (eyebrow region) was recorded. This not only captures frowning instances of a person but also detects the tension in the corrugator supercilii muscle due to thought concentration or increased mental activity. The signal was denoised and down sampled before the mean amplitude of the corrugator muscle was calculated. The parameter obtained: mean corrugator activity (C_m).
(b) **Masseter Activity.** The EMG signal from the masseter muscle (upper jaw region) was recorded. This captures the muscle movements while clenching/tightening of jaws. The signal was denoised and down sampled before the variability of the masseter muscle was calculated. The parameter obtained: masseter variability (M_V).

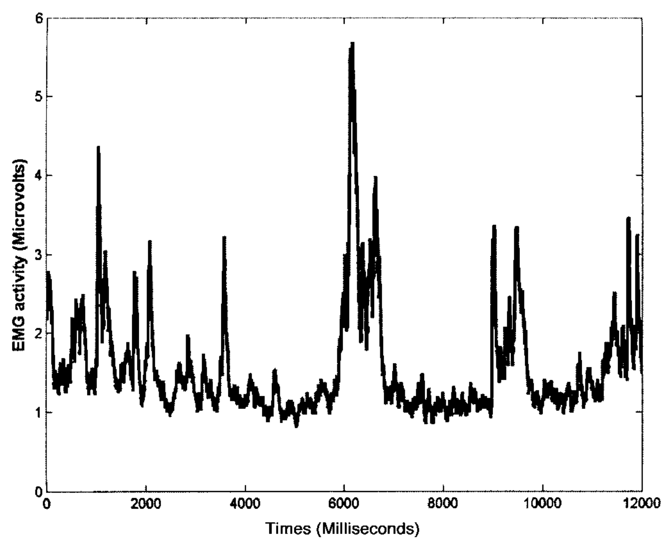

Fig. 6. A typical EMG signal.

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4. AFFECT RECOGNITION

For meaningful Human-robot interaction, it is important that the robot interprets the physiological signals of the subject intelligently to deduce his/her affective state. Our next step was to design a robust and reliable decision making system that could take in the information from the selected physiological parameters and generate an anxiety index based on this information. This index would then be used to infer the state of the human subject. Several techniques were investigated for this purpose. Since the transition from one physiological state to another is a gradual one, these states cannot be treated as classical sets, which will either wholly include a given affect or exclude it. Even within the physiological response variables, one set merges into another and cannot be clearly distinguished from another. For instance consider two affective states – a relaxed state and an anxious state. If we use the concept of classical sets a person can either be relaxed or anxious at a given instance, he cannot be both. Also the transition from one set to another is rather abrupt which does not happen in real life. In such a case, fuzzy reasoning can prove invaluable in making the decision-making process resemble human reasoning.

A series of problem-solving tasks was designed for the human companion. These included anagram solving, mathematical problem solving and auditory discrimination tasks. Using these experiments initially, we obtained pilot data to design and train a 6-input 1-output fuzzy logic system.

- Input set = $\{S_p, P_p, T_m, P_r, C_m, M_V\}$
- Output set = {*anxiety index*}
- The membership functions used: Gaussian or sigmoidal (depending upon the kind of variation these variables showed with the change in affective state.)

Fuzzy logic is based on the theory of fuzzy sets. Fuzzy set theory implements classes of data with boundaries that are not sharply defined.[19] A fuzzy set can contain elements with only a partial degree of membership. This enables the fuzzy models to exercise flexibility in capturing various aspects of vagueness in the data available to us.[30–32] Fuzzy set theoretic methods have been used extensively for pattern recognition in the past. In the present application we used fuzzy logic to identify the patterns of physiological activity, as reflected in the parameters described above, indicating anxiety.

The design and implementation of this fuzzy model involves the following steps:[33,34] (i) specifying the input and output variable membership functions, (ii) fuzzification of the input variables, (iii) defining the rule statements that relate the input variables to the output, (iv) aggregating all outputs (Fuzzy Inference), and (5) defuzzification of the output variable.

The experimental results coupled with the self-reports of the human were used to formulate a set of rules for this fuzzy system. The results of this fuzzy inference engine are presented in Section 5 where Table I shows the inputs and output for a few experiment sessions.

5. AFFECT-SENSITIVE CONTROL ARCHITECTURE

We aimed at designing a behavior-based architecture for a mobile robot system working with a human in an unknown environment. The robot would be capable of detecting and responding to affective cues from the companion. Without the affective input from the human companion this would be an ordinary exploration exercise that requires the mobile robot to perform particular tasks. However, in this case the robot was expected to behave as a living coworker to its human companion. This requires the mobile robot to respond appropriately to the affective cues from the human companion while not losing sight of the importance of its own survival and work performance. The chief requirements of the affect sensitive robotic control system under consideration are:

- Rapid reflexive responses to the changing environment
- Execution of responses in accordance to the priority associated with each response
- Navigation or workspace exploration in absence of reflex eliciting inputs from the environment.

The subsumption architecture as originally proposed by Brooks[35–37] was found to be the one most suited to build our required system upon. For the affect sensitive robotic control system under discussion, we have defined some behaviors:

Exploratory:
- Move in straight lines and turn at random angles at random times.

Table I.

Physiological Parameter	Session 1	Session 2	Session 3	Session 4	Session 5
Power (sympathetic activity)	84023.02	54180.64	278221.78	41628.53	319226.20
Power (parasympathetic activity)	28142.35	48625.93	40523.58	4762.10	29481.15
Mean phasic activity level	0.8742	0	0.66586	1.3795	0.7285
Rate of response of phasic activity	6.86	0	8.38	7.31	6.98
Mean of the corrugator activity (EMG)	1.22	11.02	9.02	7.94	6.80
Variability of the masseter activity	2.4153	1.3856	2.9474	1.9658	2.3959
Self report of the operator (scale of 9)	2.00	2.66	4.33	4.67	5.67
Anxiety index (scale of 1)	0.31	0.41	0.62	0.63	0.65

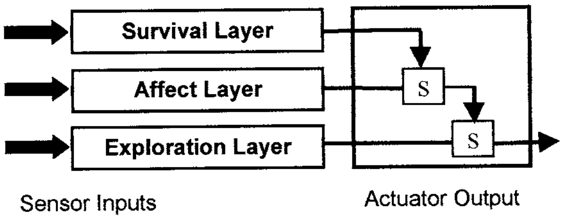

Fig. 7. Affect-sensitive subsumption architecture.

Survival:
- Turn to right and reverse if obstacle is on left;
- Turn to left and reverse if obstacle is on right;
- Reverse if obstacle is in front or on both sides.

Affective:
- Query: Ask the human companion if he/she is anxious or needs assistance of any kind;
- Report: Raise an alarm and send feedback regarding the state of its human companion to the Base Station;
- Homing: Return to the point where its human companion is working.

We have used subsumption architecture to execute these tasks in a priority-based manner, allowing one behavior to be executed at a time. Figure 7 shows that in the absence of any affective signals from its human companion and any survival-relevant signals, the robot remains in the wandering or the exploratory mode, moving around and navigating the workspace.

As it gets an affect signal from its companion indicating that he/she is anxious, the robot suspends the wandering task and enters the affect mode, wherein it rushes to the rescue of its companion or simply queries him depending upon the urgency of the situation.

If, however, the robot encounters at any time a situation that puts its own survival at stake, it will enter the survival mode, suspending either the affect or the wandering mode it is in at that instant to do the best possible task to save itself.

6. EXPERIMENT

6.1 Task Description

The goal of the experiment was to develop and implement real-time, affect sensitive human-robot co-ordination that would enable the robot to recognize and respond to the psychological states of a human. This work therefore involves online sensing of physiological indices, mathematical analysis to infer psychological states, and implementation of a robot control architecture that allows the robot to respond to psychological needs of its human companion. In this experiment we have tried to simulate under laboratory conditions a human-robot system working in close coordination on a navigation 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 individually with the robot being responsive to the astronaut's affective states (for instance stress, panic or fatigue).

The experiment consists of two major components: first, gathering pilot data to design and train a fuzzy logic-based affect-recognizer that could recognize or "understand" the physiological responses of a person and second, implementing a human-robot co-operation task consisting of a mobile robot navigating a workspace and its human companion whose physiological state is being continuously monitored. Due to the limitations in producing stress conditions in a human subject repeatedly for the purpose of human-robot co-ordination sessions, the above-mentioned two components of the experiment were conducted separately. A human subject's physiological responses under various levels of mental anxiety were recorded. Later, while conducting the human-robot co-operation experiments, this physiology data was fed to the system in the manner it would have been received from a human being in real-time.

One of the most challenging aspects of this experiment is the detection and recognition of affect signals produced by a human. We needed to design and train a fuzzy logic based affect recognizer that could recognize or "understand" the physiological responses of a person.

To generate pilot data for the above purpose we performed several experiments that generated mental stress in a human subject by involving him in cognitive activities. Such tasks that usually cause anxiety include mathematical problem solving, anagrams solving, etc. By manipulating the difficulty of the tasks that an individual is made to do, it is relatively easy to systematically produce various levels of affect, states ranging from boredom (a long sequence of trivially easy subtasks), optimal engagement (somewhat challenging subtasks), to high levels of frustration and anxiety (a sequence of highly difficult subtasks).

Biofeedback sensors were placed on the body of the person whose physiology was being monitored. A typical experimental set up is shown in Figure 8. The serial interface of MATLAB was used for online data acquisition and processing of the sensor data. There was continuous signal processing of the incoming sensor data. The signal conditioning involved filtering, smoothening, performing spectral analysis, wavelet analysis and other similar processing techniques. Each sensor channel was processed to obtain the relevant parameters from it. For instance a measure of the sympathetic and parasympathetic activities was obtained from the ECG (heart activity) signal and the mean phasic and tonic levels were extracted from the EDA (skin conductance) signal. Using all the relevant parameters of cardiac activity, electrodermal activity and electromyographic activity the affective state of the person was determined. This information was then used in implicit human-robot co-operation.

The second part of the experiment consisted of implementing a real-time human-robot interaction framework that would enable the robot to recognize the human's psychological state through continuous physiological sensing, and act accordingly to address the psychological needs of the human. The mobile robot-Trilobot[38] was used in the

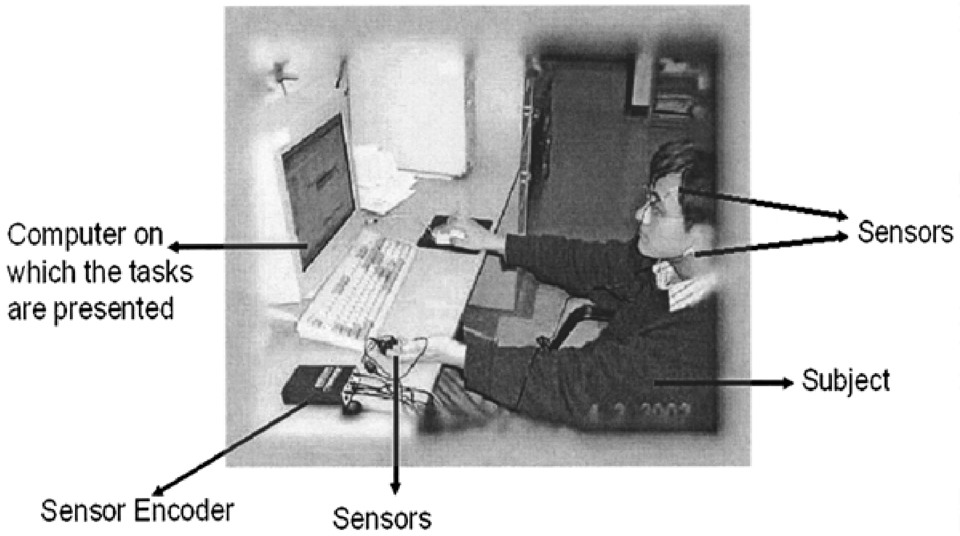

Fig. 8. Physiological monitoring of a human subject.

implementation of the human-robot co-ordination task. The robot's tasks included:

- Wandering in a random manner exploring the workspace;
- Avoiding obstacles in the workspace;
- Responding to the affect signals of the human companion.

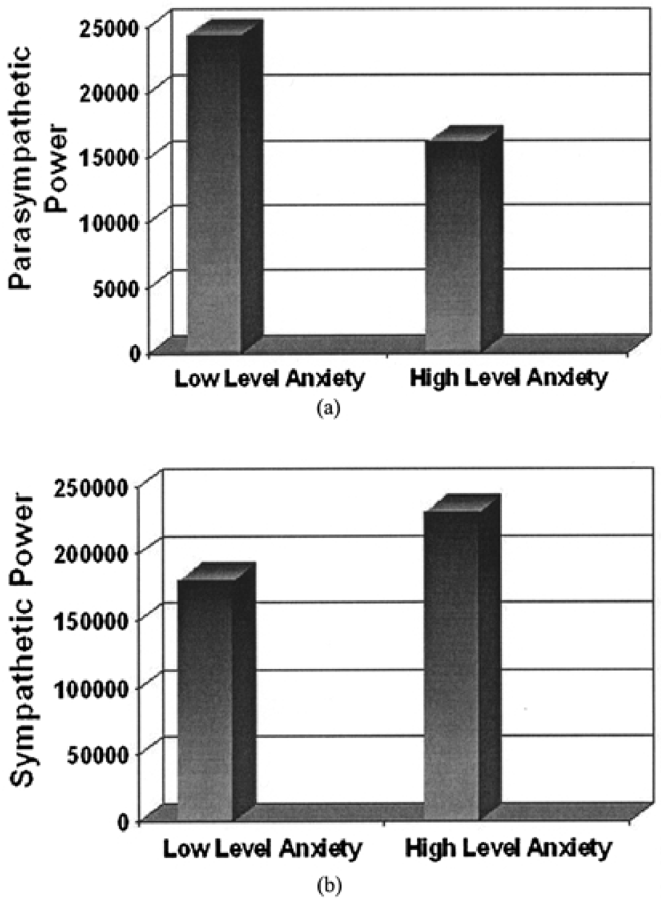

Fig. 9. Power of sympathetic activity (a) and parasympathetic activity (b) of heart under conditions of low versus high anxiety (msec^2).

The priorities and timings of the execution of the above tasks are decided by the robot's architecture, which has been discussed in detail in the previous section. At any given time the robot's sensors map its environment onto its memory. The sonar range finder and the touch sensors give information regarding the obstacles in the workspace, the compass indicates the orientation of the mobile robot, the optical encoders indicate the motor speed and distance traveled and the physiological sensors give an indication of the affect state of the human.

6.2 Results

(i) **Affect detection and recognition.** A human subject was engaged in a series of cognitive problem-solving tasks that varied in difficulty in ways that were designed to produce variations in the person's anxiety levels over the course of performing the tasks. Wearable sensors were used to continuously monitor the person's physiological activities, and the physiological parameters as mentioned in Section 3 were calculated using customized algorithms.

Using the self-report of the human doing the tasks we computed an anxiety index, which essentially indicated how anxious the person was at various points while performing the tasks. There were reliable correlations between the physiology and the person's self-reported anxiety levels. This further supported the hypothesis that there is a distinct relationship between the physiology and affective state of a person. The person's physiological activities and self-reported anxiety levels were monitored across a total of approximately 50 different task intervals. To illustrate the differences in physiological activity associated with high versus low anxiety for this person, the two intervals that corresponded to the lowest level of self-reported anxiety and

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the highest level of self-reported anxiety index were examined. The physiological activities associated with these intervals are presented in Figures 9–11.

Cardiac activity was a strong indicator of anxiety. The power in the sympathetic activity frequency range increased and the power in the parasympathetic activity frequency range decreased as the human subject showed anxiety (Figure 9). There was marked increase in the mean amplitude of skin conductance responses with increased anxiety (Figure 10a). The rate of these responses also increased (Figure 10b). Similar increases were observed in the mean level of corrugator activity, and in the variability of masseter activity (Figure 11).

Once a pattern had been established between the physiological responses and the affective state, a fuzzy logic decision-making system was designed to infer the affective state given a particular set of responses. Table I shows the results of testing the fuzzy logic system on five blocks of pilot data that were obtained from the problem-solving task sessions. The self-reports of the subject are also indicated in the table so that we can evaluate the anxiety index generated by the fuzzy system against this measure of the person of his own anxiety. We observed that there was an appreciable correlation between the anxiety index that the fuzzy decision making system generates and the self-report of anxiety of the subject. Five sessions have been selected to demonstrate the robustness and reliability of the fuzzy system. The fine-tuning of the weight of each rule and alternation of the shape of the membership functions were performed until very accurate results were obtained.

(ii) **Robot Behavior.** Three triggers were continuously generated using the feedback from the robot's environment. These were also evaluated in a continuous fashion by the mobile robot as it assessed its surroundings and decided the next course of action. The triggers mentioned above were: the survival trigger (which when triggered indicated any immediate danger to the robot's own safety at any given instant), the affect trigger (which when triggered indicated that its human companion was above some threshold level of anxiety) and the wander trigger (which when triggered indicated that the mobile robot was expected to be in its wander mode, i.e. carrying on the exploration task unimpeded). By default the mobile robot would be wander triggered at all times.

At any given instant the mobile robot received one or all of the three triggers. The decision regarding the

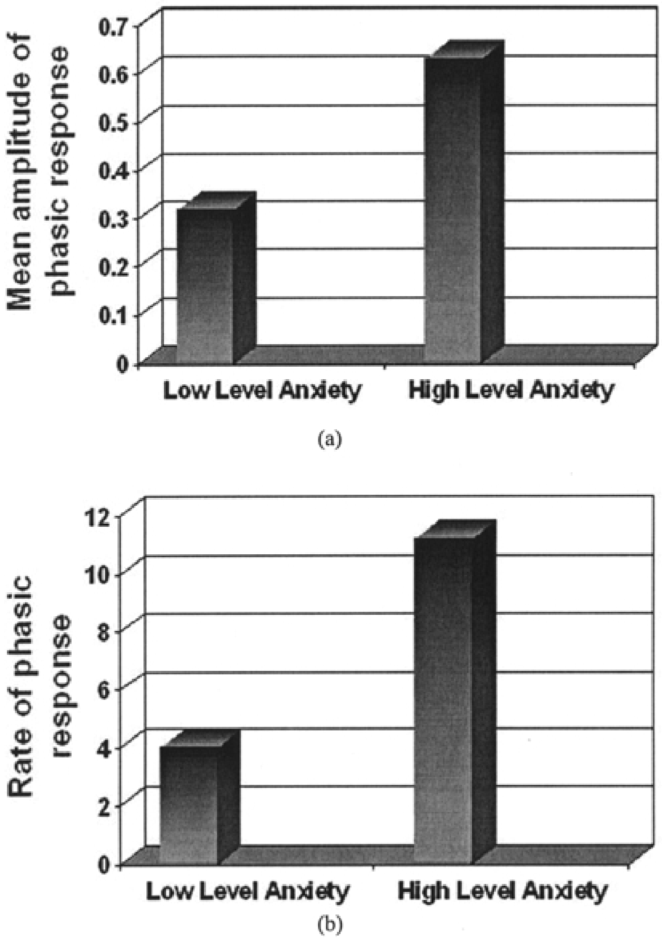

Fig. 10. (a) Mean level of phasic activity and (b) Rate of response of phasic activity in states of low versus high anxiety.

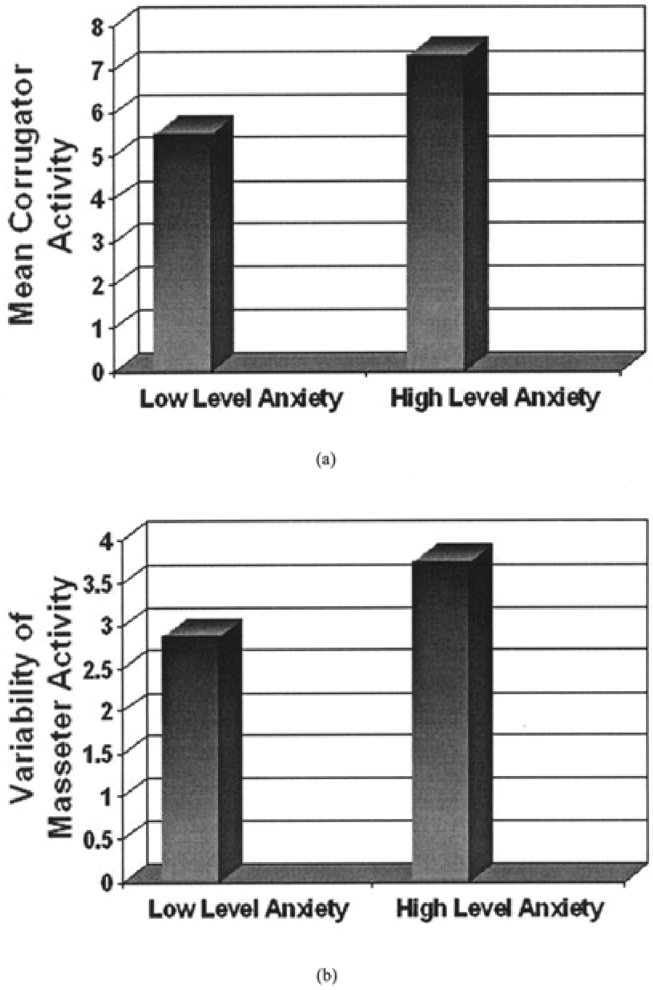

Fig. 11. (a) Mean activity of the corrugator muscle and (b) Variability of the masseter muscle in states of low versu high anxiety.

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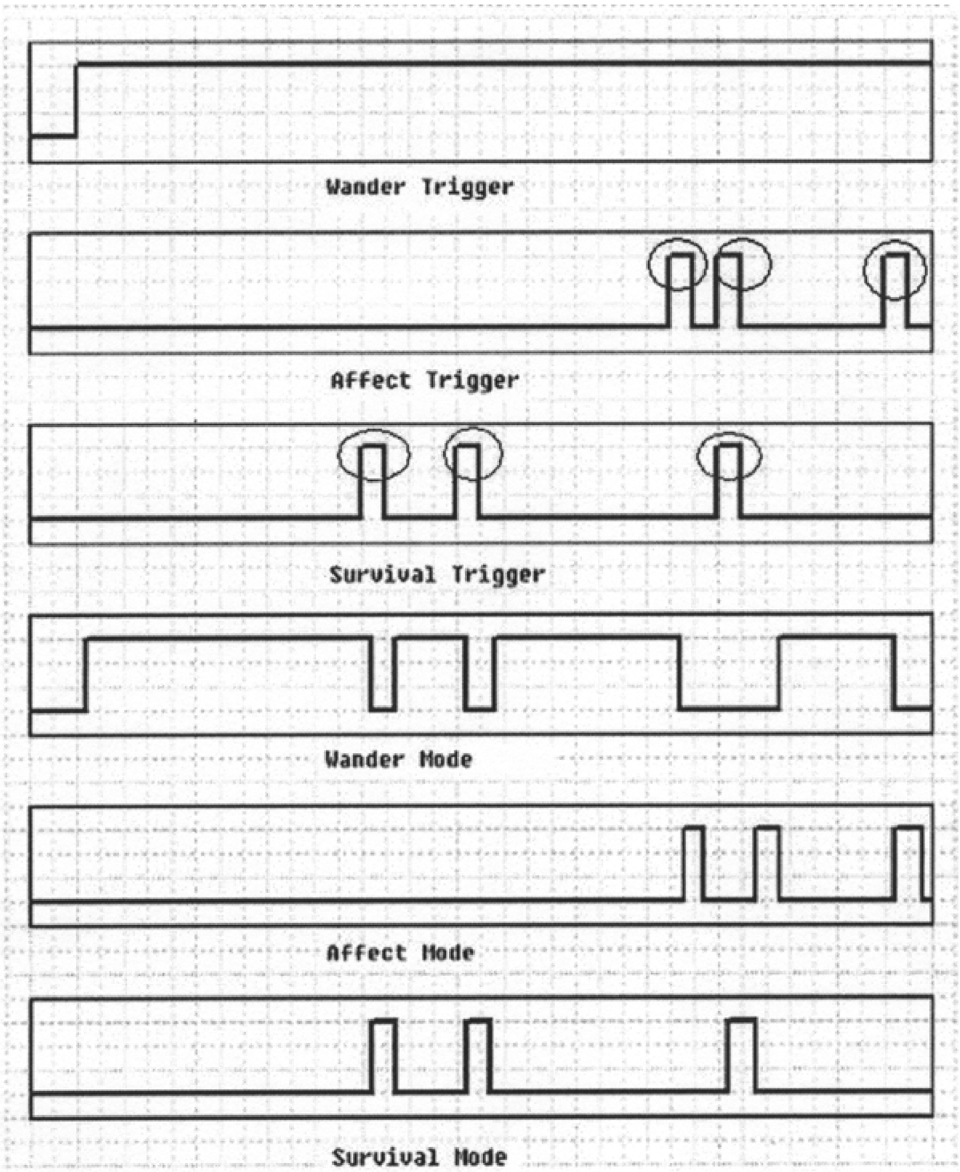

Fig. 12. Timing diagram of the triggers that are received by the robot and the modes activated by those.

trigger that will be processed first was decided by the robot's architecture that has been discussed in detail in Section 3. A trigger that was being processed caused the robot to go into that particular mode. For instance if the robot was processing the affect trigger then the robot would go into the affect mode in which it would do any particular task or sequence of tasks that enabled it to respond to that situation in the best possible manner. The affect mode included tasks like assisting the companion in navigation, querying its companion about his/her well being, locating its companion in the workspace and returning to him/her or simply raising an alarm.

One of the timing diagrams as obtained from a 15-minute experiment session is shown in Figure 12. As seen in Figure 12, in absence of any affect or survival trigger the only trigger that remains active is the wander trigger, as a result of which the robot stays in the wander mode. As soon as any survival trigger is received, it suppresses the wander trigger or it assumes priority over the wander trigger. As a result the robot receives the survival trigger at that instant.

The robot immediately goes in to the survival mode, thereby suspending the wander mode tasks that it had been performing till that instant. Now that the robot is in the survival mode it diagnoses the nature of threat it faces and takes some steps to get out of that threatening situation. For example, if the robot hits an obstacle in front of it, its sensors will provide it with accurate information regarding this and the robot will back up and steer itself away from the obstacle. Similarly if the robot while in the wander mode detects that the affect trigger is activated, it will forego the navigation task and activate the affect mode wherein it will respond to the need of its human companion.

It might query, assist or alert its companion depending on the nature of the affect that the root has detected. Here the affect states of the human subject that might

https://doi.org/10.1017/S0263574703005319 Published online by Cambridge University Press

activate the affect trigger are low, medium or high level of anxiety. Sometimes the survival trigger and the affect trigger get activated simultaneously. In such cases the robot will first process the survival trigger and place the affect trigger in waiting. After it has taken a suitable action to get out of a threatening situation, it will process the affect trigger.

7. CONCLUSION

We proposed an innovative theoretical, computational and experimental approach drawing from emerging results from affective computing, psychology, and advanced control theory to develop a human-robot interaction framework that is affect-sensitive and is capable of addressing affective need. We have demonstrated through experiments an implicit communication between a human and robot wherein the robot detects and recognizes anxiety in its human companion and changed its task sequence to accommodate a suitable response.

Successful affect recognition results were obtained from physiological responses alone in spite of the absence of multiple modalities, for instance voice, gesture and posture. As an important part of the future work, affect detection and recognizing algorithms will be made more robust by testing them with more physiology data from human subjects. Its reliability will be tested not only over the same subject but also over multiple subjects. A context analyzer that realistically investigated the cause of some affect shown by a human and prompted the robot to take corrective actions would be the next big step towards an advanced level of human-robot interaction.

ACKNOWLEDGEMENTS

The work was partially supported by the NSF grant IIS-0107775, NASA grant NAS5-98051 (07600100) and the Vanderbilt University Discovery grant.

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