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Physiological and subjective responses to articulated robot motion

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SUMMARY
This paper describes the implementation and validation of a fuzzy inference engine for estimating human affective state in real-time, using robot motions as the stimulus. The inference engine was tested with 36 subjects. To the authors' knowledge, this paper reports the first such trial that measures affective response to human-scale physical robot motions for a statistically significant population. The results demonstrate that affective state arousal can be detected using physiological signals and the inference engine. Comparison of results between the two planners shows that subjects report less anxiety and surprise with the safe planner.

KEYWORDS: Physiological signal monitoring; Affective state estimation; Human–robot interaction.

1. Introduction

As robot manipulators move from isolated work cells to unstructured and interactive environments, they will need to become better at acquiring and interpreting information about their environment.[1] Particularly, in cases where human–robot interaction is planned, human monitoring can enhance the safety of the interaction by providing additional information to robot planning and control systems.[2,3] Example applications include robots that perform home-care/daily-living tasks,[4] such as dish-clearing (removing dishes from a table and stacking them in a dishwasher),[5] co-operative load carrying,[6,7] and feeding.[8,9]

During human–human interaction, non-verbal communication signals are frequently exchanged in order to assess each participant's affective state, focus of attention, and intent. Many of these signals are indirect; that is, they occur outside of conscious control. By monitoring and interpreting indirect signals during an interaction, significant cues about the affective state of each participant can be recognized.[10] Recently, research has focused on using non-verbal communication, such as eye-gaze,[2,3] facial expressions,[11,12] and physiological signals[10,13–16] for human–robot and human–computer interactions. Although not used during interpersonal interaction, physiological signals are particularly well-suited for human–robot interaction, as they are relatively easy to measure and interpret using on-line signal processing methods.[14–16] By using non-verbal information such as physiological signals, the robot can estimate user approval of its performance without requiring the user to continuously issue explicit feedback.[2,3] In addition, changes in some non-verbal signals precede a verbal signal from the user. Observation of physiological information can allow the robot control system to anticipate command changes, creating a more responsive and intuitive human–robot interface.

The focus of this research is to determine if physiological signals are suitable for use during human–robot interaction. A small feasibility study[17] showed promise in using physiological signals to estimate affective state when robot motion is the stimulus. Based on that study and existing physiological research,[18–21] in this work, a fuzzy inference engine is proposed to estimate affective state on-line. In this paper, this inference engine is validated on a statistically significant sample (36 subjects). The goals of this research are twofold: first, to develop and test a reliable system for estimating user reaction to robot motion, and second, to determine if the perceived safety of the motion can be related to the type of path planning used to generate the robot motion.

1.1. Related work

Physiological monitoring systems have previously been used to extract information about the user's reaction, both for human–computer and human–robot interactions. Signals proposed for use in human–computer interfaces include skin conductance, heart rate, pupil dilation, and brain and muscle neural activity. Bien *et al.*[22] advocate that soft computing methods are the most suitable methods for interpreting and classifying these types of signals, because these methods can deal with imprecise and incomplete data.

Sarkar[16] proposes using multiple physiological signals to estimate affective state, and using this estimate to modify robotic actions to make the user more comfortable. Rani *et al.*[15,23] use heart-rate analysis and multiple physiological signals to estimate human stress levels. In Rani *et al.*,[15] the stress information is used by an autonomous mobile robot to return to the human if the human is in distress. In that example, the robot does not directly interact with the human; instead, prerecorded physiological information is used to allow the robot to assess the human's condition in a simulated rescue situation. In these studies, video game playing, and not robot motion, is used to elicit the physiological response.

Wada *et al.*[24] and Saito *et al.*[25] have used a small robotic seal to measure the physiological effects on elderly patients in a nursing home. In their work, 23 patients were tested, using both subjective responses to a questionnaire, and measuring physiological changes in stress level through urinary tests. The effects of the robot on the nursing staff were also examined. In that case, a physical robot was used to elicit

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the psychological and physiological response; however, the physiological effects of the seal robots were not estimated on-line, but off-line through the subsequent use of questionnaires and urine samples.

Kanda *et al*.[26] studied human responses to robot motion during a human–robot interaction study with a humanoid mobile robot. In this study, 26 subjects were asked to interact with the robot. Their reactions to the robot were elicited via a post-experiment questionnaire. The relationship between the subjective evaluations, eye contact, and robot motion was then analyzed. It was found that well-coordinated robot behaviors correlate with a positive subjective evaluation. In this study, only positive subjective evaluation was analyzed, and fear and anxiety were not reported. In addition, human response was not measured on-line.

Nonaka *et al*.[27] describe a set of experiments where human response to pick-and-place motions of a virtual humanoid robot was evaluated. In their experiment, a virtual reality display was used to depict the robot. Human response was measured through heart rate measurements and subjective responses. No relationship was found between the heart rate and the robot motion, but a correlation was reported between the robot velocity and the subject's rating of "fear" and "surprise."

Koay *et al*.[28] describe an early study where human reaction to robot motions was measured online. In this study, 28 subjects interacted with a robot in a simulated living room environment. The robot motion was controlled by the experimenters in a "Wizard of Oz" setup. The subjects were asked to indicate their level of comfort with the robot with a handheld device. The device consisted of a single slider control to indicate comfort level and a radio-signal data link. Only data from seven subjects was considered reliable, and included in subsequent analysis. Analysis of the device data with experiment video found that subjects indicated discomfort when the robot was blocking their path, the robot was moving behind them, or the robot was on a collision course with them.

Most of the studies using physiological sensors to date have used virtual environments such as a video game,[15,23] or a virtual robot[27] to simulate an interaction situation. Studies with physical human–robot interaction[24,26,28] have used subjective responses and other off-line methods to analyze user response. To the authors' knowledge, no studies have been performed to date to test methods suitable for real-time affective state estimation using robot motion as the stimulus.

In this work, an affective state inference engine is developed for online estimation of the affective state. The inference engine is validated through human trials, using robot motions of an articulated manipulator performing typical interaction tasks as the stimulus. The paper is organized as follows: The fuzzy inference engine and physiological signal selection and preprocessing is described in Section 2. The experimental approach is described in Section 3, and results are detailed in Section 4. Section 5 concludes the paper and outlines directions for future research.

2. Affective state inference

The affective state is estimated based on measured physiological signals such as heart rate, skin conductance, and facial muscle contraction. An important question when estimating human affective response is how to represent the affective state. Two different representations are commonly used in emotion and emotion-detection research: one using discrete emotion categories (anger, happiness, fear, etc.), and the other using a two-dimensional representation of valence and arousal.[29] Valence measures the degree to which the emotion is positive or negative, and arousal measures the strength of the emotion. The valence/arousal representation adopted herein appears adequate for the purposes of robotic control, and is easier to convert to a measure of user approval. This representation system has also been favored for use with physiological signals and in psychophysiological research.[10,18,29,30]

Three physiological signals were selected for measurement: skin conductance response (SCR), heart rate, and corrugator muscle activity. These three signals have been shown to be the most reliable indicators of affective state in psychophysiological research.[10,18,30] Respiration rate was also considered in an early study,[13] but was rejected as unsuitable for online interaction applications due to the slow physiological response of the signal.

SCR is a strong indicator of affective arousal. Several studies[18,21,30] have shown that skin conductance is positively correlated with arousal. Bradley and Lang[18] report that 74% of subjects exhibit this correlation.

Corrugator muscle activity measured via electromyogram (EMG) is negatively correlated with valence. The corrugator muscle, located just above each eyebrow close to the bridge of the nose, is responsible for the lowering and contraction of the brows, i.e., frowning, which is intuitively associated with negative valence. Bradley and Lang[18] reported corrugator muscle activity levels that were well above the baseline level for negative valence stimuli, slightly above baseline level for neutral valence stimuli, and slightly below baseline level for positive stimuli. In their study, more than 80% of subjects showed this correlation.

Unlike the SCR and corrugator EMG response, heart activity is governed by many variables, including physical fitness, posture, and activity level as well as affective state. The heart muscle, unlike the electrodermal system, is enervated by both the parasympathetic and the sympathetic nervous system.[29] The heart muscle also has homeostatic and metabolic functions aside from emotional perception, unlike facial muscle EMG.[29] The correlation between heart activity and affective state is therefore more modest,[29] and conflicting results have been reported in the psychophysiological research. In tests using external stimuli to generate the affective response (such as picture viewing), heart rate response is initially decelerative, followed by a subsequent acceleration, while tests using internal stimulus (recalling emotional imagery) showed an initial accelerative response.[18] Using these results, heart rate deceleration is associated with the orienting response (i.e., increased arousal). Heart rate at the baseline, with no heart rate acceleration or deceleration is associated with low arousal, while high heart rate and heart rate acceleration/deceleration are associated with high arousal.

Another key finding from psychophysiological research is that physiological responses can be highly variable

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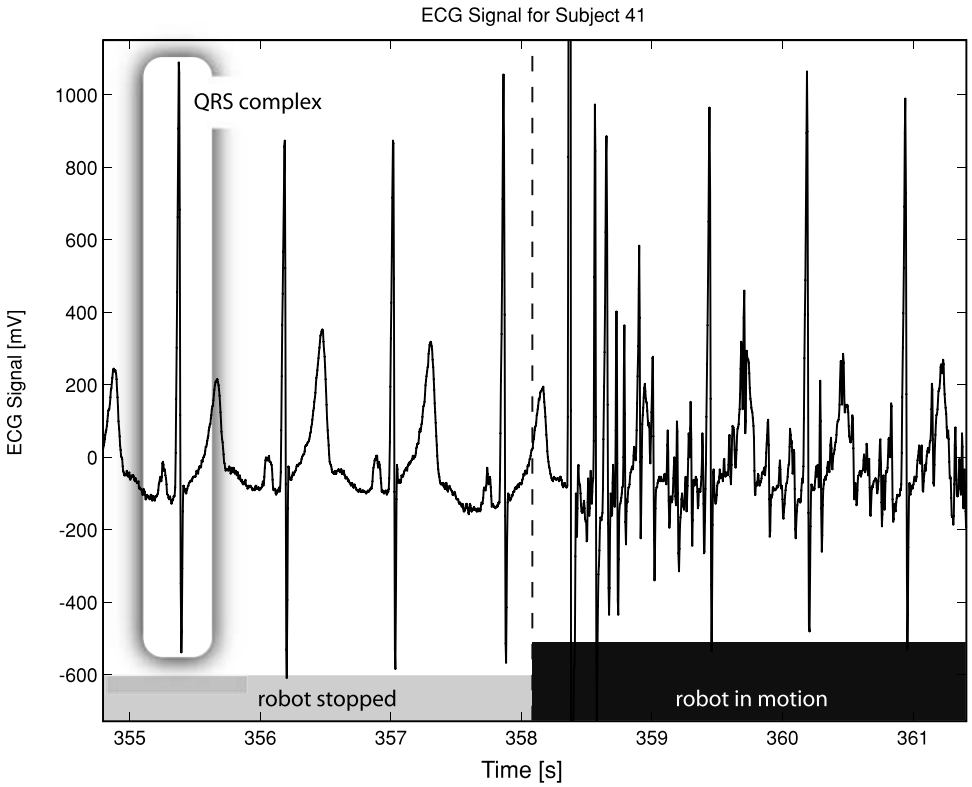


Fig. 1. Heart rate signal for subject 41.

between individuals, as well as variable for the same individual depending on the context of the response.[18–20] Pre-processing of the data is necessary prior to inference, in order to extract the relevant features of the signals and to normalize the signal features so that a single inference engine can be used across individuals. The pre-processing of the selected signals is discussed later. Then, the fuzzy rulebase developed on these signal features is discussed in Section 2.2.

2.1. Data processing and feature extraction

2.1.1. Heart rate. Heart activity is measured by measuring the electrical signal of the heart muscle through an electrocardiogram (ECG). The first 3 s of the ECG signal shown in Fig. 1 show a typical signal with the repeated QRS complex. The QRS complex corresponds to the electrical current that causes contraction of the left and right ventricles of the heart, and in a typical ECG signal are the most clearly identifiable features.

The ECG signal is then analyzed to extract the heart rate. The algorithm and open source code from Hamilton and Tompkins[31] are used to extract the heart rate. The algorithm first performs band-pass filtering on the raw ECG signal; the signal is then differentiated and smoothed by an 80-ms moving average window. Peaks are then detected in the resulting signal, and detection heuristics are applied to avoid detecting multiple peaks for a single heart beat. These rules include enforcing a minimum interval of 200 ms between peaks, and checking for QRS wave characteristics (i.e., both positive and negative slopes in the raw signal) to ensure that a change in the baseline voltage (due to subject movement) is not misclassified as a peak. The algorithm also automatically determines the threshold at which a peak should be considered a beat. The algorithm detects a heartbeat with an average delay of 0.36 s. Although this algorithm is quite robust, noise caused by excessive subject movement can cause the beat detection to fail. Some subjects will move their torso suddenly (i.e., flinch) when presented with a rapid robot motion. The muscle contractions in the shoulder and abdominal muscles during the torso motion introduce noise to the ECG signal causing additional beats to be detected. Figure 1 shows a typical signal during a sudden motion by the subject. The start of robot motion is indicated with the square-wave signal (low: stopped, high: moving). To eliminate the spurious effects of sudden movements, a check is performed after the heart rate is calculated. If the generated heart rate is more than 30 beats per minute (bpm) higher in magnitude from the previously averaged heart rate, the generated heart rate measurement is discarded and the previous measurement used. Since the average change for heart rate in this type of experiment is expected to range from 2 to 15 bpm (change from baseline),[29] this threshold is well above the rate of change that could be seen in a genuine heart acceleration.

Once a beat is detected, the beat-to-beat time is used to calculate the heart rate. The heart rate is then smoothed using a three-sample averaging filter. The average heart rate is also updated. The signal is then normalized to the $[-1, 1]$ range based on the average heart rate

$$h_{\mathrm{n}} = \frac{h - h_{\mathrm{avg}}}{h_{\max} - h_{\min}}, \tag{1}$$

where h_{n} is the normalized heart rate, h is the measured instantaneous heart rate (which has been preprocessed with

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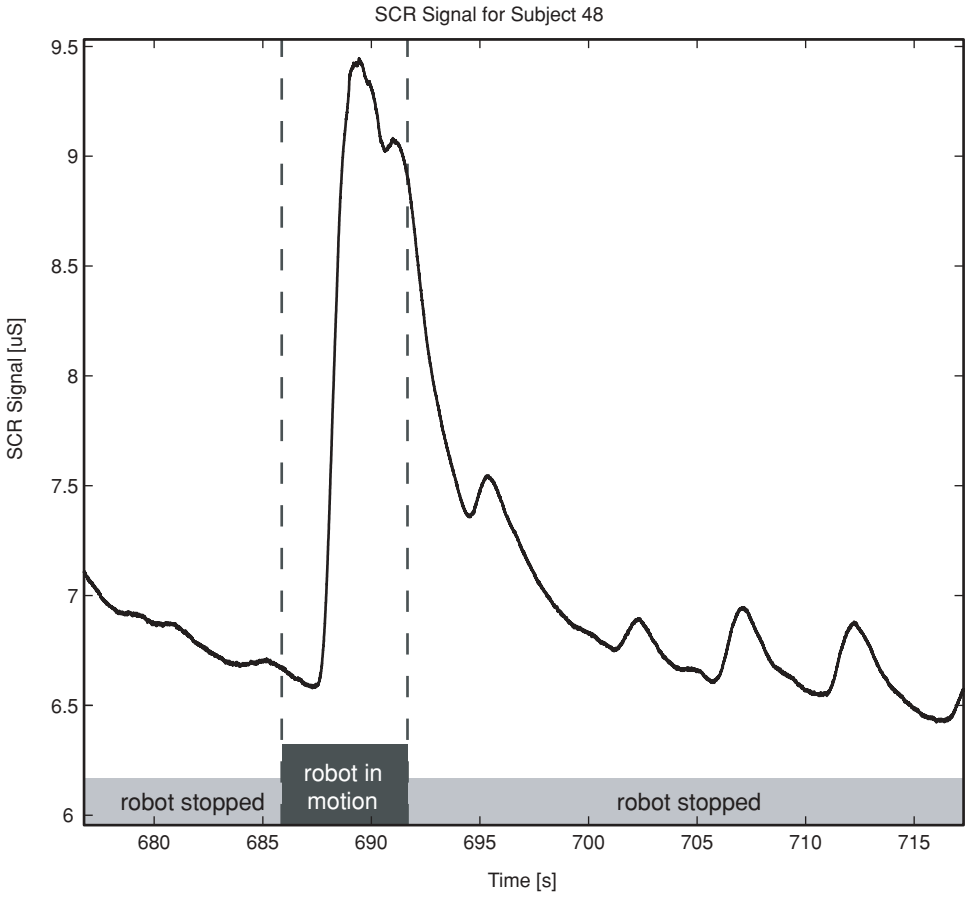


Fig. 2. Typical SCR response (subject 48).

the smoothing filter), h_{avg} is the average heart rate, and h_{min} and h_{max} are the minimum and maximum heart rate, respectively. To generalize the normalization across subjects, $h_{\text{min}} = 0.7h_{\text{avg}}$ and $h_{\text{max}} = 1.5h_{\text{avg}}$ are used, where h_{avg} is computed separately for each subject.

The inference engine also uses the heart rate acceleration to detect accelerative or decelerative periods at the start of an affective response. The heart rate acceleration is calculated by differentiating the smoothed heart rate signal. The heart rate acceleration is normalized to range between [−1, 1], based on the normal heart rate acceleration range.[19]

$$a_{\text{n}} = \frac{a}{|a_{\text{max}}|}, \tag{2}$$

where a_{n} is the normalized heart rate acceleration, a is the raw instantaneous heart rate acceleration, and a_{max} is the maximum observable heart rate acceleration.[19] The value of a_{max} used was a change of 16 beats per sample.

Recent research[15,23] has reported the use of frequency domain heart rate analysis for use in affective state estimation. However, since heart rate data is very slow (around 1 Hz), using frequency windowing methods such as windowed Fourier analysis or wavelets results in multisecond delays, rendering the data unsuitable for real-time interaction.

2.1.2. Skin conductance response. SCR is measured by passing a small current between two electrodes placed on two fingers (of the same hand), and measuring the conductance. Increased perspiration tends to increase the measured conductance. A typical SCR response to robot motion is shown in Fig. 2. Both the baseline level of SCR and the magnitude of response are highly variable between individuals. Note that in addition to the specific SCR response (i.e., response to a stimulus), the SCR signal frequently exhibits non-specific responses (for example, the smaller peaks following the specific response peak).

Two features were extracted from the SCR: the level of SCR and the rate of change of SCR (dSCR). Normalization of the SCR signal is problematic, because the baseline level of the signal tends to drift, and SCR response is habituating. In previous studies,[13,17] the data was normalized to a range between [0, 1] using baseline data,[13] or using the minimum and maximum values in the preceding 30 s.[17] When using baseline data, the normalization fails to account for signal drift. Normalization using only the data in the preceding 30 s produces long periods of saturation in the normalized signal. For example, following a long period of low-amplitude response, a large response will tend to saturate the normalized signal for several seconds, thus not giving an accurate normalized signal. To avoid saturation, a bandpass filter was used instead to remove both the low-frequency drift and the high-frequency measurement noise. A [0.5 Hz, 5 Hz] third-order Butterworth filter was used to perform the filtering. The normalized signal was generated

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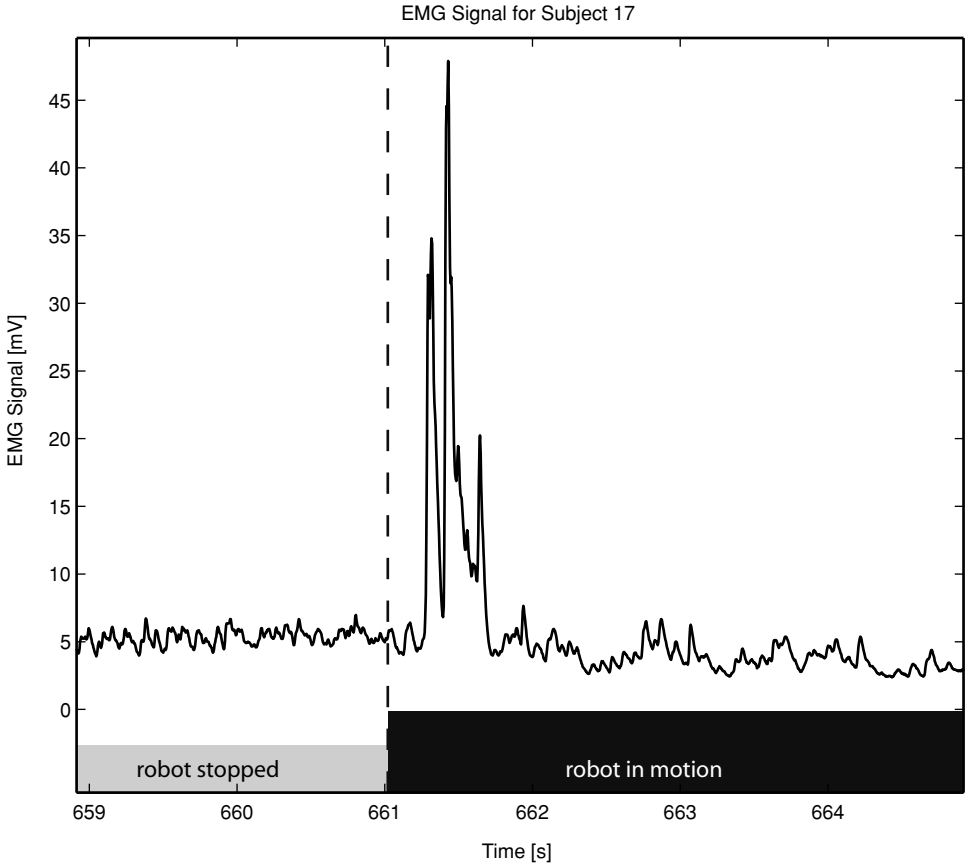


Fig. 3. EMG signal for subject 17.

as shown here

$$s_{\mathrm{n}} = \frac{s}{s_{\max}}, \tag{3}$$

where s_{n} is the normalized skin conductance, s is the instantaneous skin conductance (preprocessed with the bandpass filter), and $s_{\max}$ is the maximum skin conductance for the subject. The best results are obtained when $s_{\max}$ is known for a subject *a priori* (through previous tests with the robot); however, when the system is being used with an unknown subject, a good estimate for $s_{\max}$ based on experimental data is obtained as

$$s_{\max} = 0.2 + 2.3\,(s_{\mathrm{resting}})_{\max}, \tag{4}$$

where $(s_{\mathrm{resting}})_{\max}$ is the maximum value of the SCR signal during the initial (resting) phase of the trial. This estimate is based on data from our feasibility study,[17] and was subsequently confirmed by post-processing of the data obtained in this study. The relationship between the maximum resting value of the SCR and the maximum SCR value during high arousal is fairly linear, with a correlation coefficient of 0.89. The value of $s_{\max}$ can then be adjusted during robot operation as more data is acquired for the subject.

Prior to calculating the dSCR, the raw SCR data is lowpass filtered with a fifth-order 5-Hz Butterworth filter. The dSCR response is then calculated by differentiating the filtered SCR data and normalizing so that the data ranges from [-1, 1] based on the normal range of rise times for the SCR.[20] The value used for the normalization factor was 0.005 of the difference between the maximum and minimum SCR levels for the subject. The inference engine is robust to changes in the normalization procedure for the slope of the dSCR, as only the direction of the slope is input to the inference engine (i.e., the signal increasing or decreasing) and not the magnitude.

2.1.3. Corrugator muscle activity. Corrugator muscle activity was measured using an EMG, which measures the electrical activity in the muscle during contraction. The EMG response is shown in Fig. 3.

One feature was extracted from the corrugator muscle EMG data: the level of response, CorrugEMG. The EMG data was low-pass filtered and smoothed using a fifth-order Butterworth filter with a cut-off frequency of 5 Hz. The data was normalized to a range between [0, 1], based on the resting EMG level measured during the initialization phase, as shown here

$$c_{\mathrm{n}} = \frac{c - c_{\mathrm{rest}}}{5c_{\mathrm{rest}}}, \tag{5}$$

where c_{n} is the normalized corrugator EMG, c is the current (filtered) measured value of the corrugator EMG and c_{rest} is the resting corrugator EMG level measured during the initialization phase.

2.2. Fuzzy inference engine

The resulting five features (heart rate, heart rate acceleration, SCR, rate of change of skin conductance, and corrugator muscle response) were input into a fuzzy inference engine to estimate the affective response of the subject. The fuzzy rule-base used to estimate the affective state is similar

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to the rule-base reported elsewhere.[13,17] The initial rule-base developed by Kulić and Croft[13] was developed for a different set of physiological sensors. For that study, respiratory activity was measured, and a blood volume pressure sensor was used to measure the heart rate instead of the ECG sensor. In addition, picture viewing, rather than robot motion was used as the stimulus. The fuzzy inference engine developed for the initial study included a rule set handling the relationship between the respiratory activity and the affective state, and the relationship between the vasomotor activity and the arousal. However, results from that study showed that respiratory activity is not a suitable physiological sensor for real-time affective state estimation, due to the slow rate of change for this signal. In addition, heart rate obtained from the blood volume pressure sensor was not as accurate as ECG, and no correlation was observed between the vasomotor activity and the arousal. In the subsequent feasibility study,[17] the blood volume pressure sensor was replaced by the ECG sensor, and the respiration sensor was not used. This study was the first to use robot motion as the stimulus, rather than picture viewing. The rulebase was modified to handle the change in the sensor and signal type. Based on the result of this initial feasibility study, the rulebase was further refined to remove conflicting rules and minimize the potential for false positives. In addition, the signal conditioning and preprocessing of the input features was modified, as discussed in Section 2.1.

The five extracted features (HeartRate, HRAccel, SCR, dSCR, and CorrugEMG) were fuzzified using simple trapezoidal input membership functions. The outputs of the fuzzy engine were the estimated valence and the estimated arousal. The fuzzy inference engine outputs an estimate of the affective state at every sample (i.e., 256 Hz); however, there is some delay between the physiological response and the estimated valence and arousal, due primarily to the delay in heart rate estimation, as discussed in Section 2.1.1.

Table I shows the rule-base for the system. This rule-base was derived using data from psychophysiological research.[18–21,30] Physiological responses can be highly variable between individuals, as well as variable for the same individual depending on the context of the response. In addition, not all subjects present with the same physiological response. For example, 74% of subjects exhibit a correlation between SCR and arousal.[18] Therefore, the rule-base was structured in such a way that reliable outputs would be obtained even if a subject did not exhibit all of the responses characterized by existing research. For this reason, each input was handled with separate rules (e.g., if SCR: HIGH then AR: HIGH), rather than combining indices (e.g., if SCR: HIGH and HR: HIGH, then AR: HIGH).

In Table I, rules 1–8 encapsulate the relationship between the SCR and arousal. If the skin conductance is high or increasing, arousal is high. Rules 9–13 describe the relationship between corrugator muscle EMG and valence. High corrugator muscle activity corresponds to negative valence, while very low corrugator muscle activity (below the resting level) indicates positive valence. Rules 14–17 relate heart activity to the affective state. Constant heart rate at the baseline corresponds to low arousal, while high heart rate and heart rate acceleration are associated with high arousal.

Table I. Fuzzy inference engine rulebase.

1. If (SCR is ZERO) and (dSCR is ZERO) then (Arousal is LOW)
2. If (SCR is LOW) and (dSCR is NEG) then (Arousal is LOW)
3. If (SCR is LOW) and (dSCR is ZERO) then (Arousal is LOW)
4. If (SCR is LOW) and (dSCR is POS) then (Arousal is MED)
5. If (SCR is MED) then (Arousal is MED)
6. If (SCR is HIGH) then (Arousal is HIGH)
7. If (SCR is ZERO) and (dSCR is NEG) then (Arousal is LOW)
8. If (SCR is ZERO) and (dSCR is POS) then (Arousal is MED)

9. If (CorrugEMG is NEG) then (Valence is POS)
10. If (CorrugEMG is ZERO) then (Valence is ZERO)
11. If (CorrugEMG is LOW) then (Valence is ZERO)
12. If (CorrugEMG is MED) then (Valence is NEG)
13. If (CorrugEMG is HIGH) then (Valence is VNEG)

14. If (HeartRate is VNEG) then (Arousal is HIGH)
15. If (HRAccel is VNEG) then (Arousal is MED)
16. If (HeartRate is VPOS) then (Arousal is HIGH) (Valence is NEG)
17. If (HRAccel is VPOS) then (Arousal is HIGH) (Valence is NEG)

Due to the additional variables affecting heart rate response, heart rate rules were underweighted relative to the SCR and EMG rules.

3. Experiments

The fuzzy inference engine was tested in a human–robot interaction trial. The experiment was designed to generate various robot motions and to evaluate both the human subjective response and physiological response to the motions. The affective state was estimated on-line during the experiment, using the inference engine described in Section 2.

3.1. Experimental method

The experiment was performed using the CRS A460 six degree-of-freedom (DOF) manipulator, shown in Fig. 4 from the test subjects' point of view, and in Figs. 6–9. The CRS A460 is a typical laboratory-scale robot with a payload of 1 kg, which is suitable for performing table-top assistive activities. A group of 36 human subjects were tested; 16 were female and 20 were male. The age of the subjects ranged from 19 to 56 years, with an average age of 29.2 years. Approximately half of the subjects were recruited from the students and staff of the Mechanical Engineering Department and the University of British Columbia, and the other half were recruited off-campus. The subjects were also asked to rate their familiarity with robots on the Likert scale, with 1 indicating no familiarity, and 5 indicating excellent familiarity. Of the 36 subjects, 17 had little or no familiarity with robots (response of 1 or 2), 11 had moderate familiarity (response of 3), and 7 had high familiarity (response of 4 or 5). Each subject was tested once over a contiguous time

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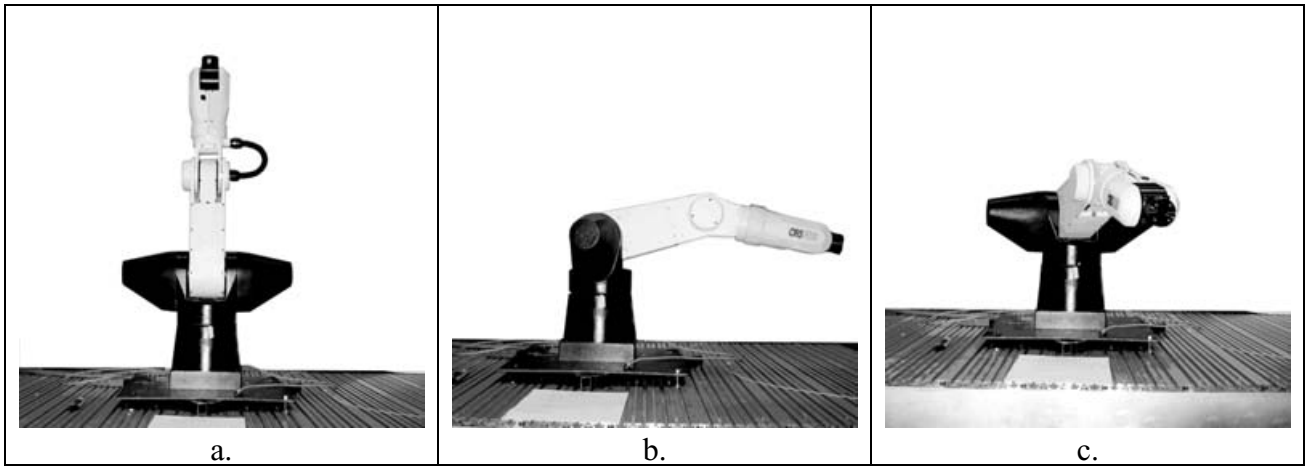


Fig. 4. Robot task positions (a: robot start/end position; b: pick position; c: place/reach position).

period of approximately 25 min. Single trials of multiple subjects were selected over multiple trials of a single subject in order to capture a general response to the robot motions.

3.1.1. Trajectory generation. Two different tasks were used for the experiment: a pick-and-place motion (PP), similar to the trajectory displayed to the subjects in Nonaka *et al.*[27] and a reach-and-retract motion (RR). These tasks were chosen to represent typical motions an articulated robot manipulator could be asked to perform during human–robot interaction, for example, during hand-over tasks. For the pick-and-place motion, the pick location was specified to the right and away from the subject, and the place location was directly in front and close to the subject. For the reach-and-retract motion, the reach location was the same as the place location. For both the tasks, the robot started and ended in the "home" upright position. Each of the selected positions is shown (from the subject's point of view) in Fig. 4. The main difference between the two tasks is the approach direction of the robot. For the PP task, the robot approaches the subject from the side, while during the RR motion, the robot approaches the subject from head on.

Two planning strategies were used to plan the path of the robot for each task: a conventional potential field (PF) method with obstacle avoidance and goal attraction,[32] and a safe path method (S) reported elsewhere.[33] The two planners were used to plan the same two tasks (i.e., the starting and ending robot positions are the same for both planners, while the robot configurations at intermediate points are different). The robot is closest to the subject at one of the final locations; however, there is no possibility of the robot contacting the subject, as the subject is located outside of the robot workspace. The safe path planner is similar to the potential field method, with the addition of a danger criterion, comprising of factors that affect the impact force during a collision between the robot and the human that is minimized along the path. This type of planning results in the robot lowering its inertia along the path, and maximizing the distance between the robot and the person along the path. Point-to-point planning was not used, as this type of planning would not be suitable for an interactive, human environment, where obstacles may be present on the straight line between the current robot location and the target location. The same PP and RR end-effector targets were used for both the planners. The four motions tested are detailed in Table II. Figures 5–8 show frames of video data depicting each motion type.

Table II. Test path naming and descriptions.

Path	Description
PP-PF	Pick-and-place task planned with potential field planner
PP-S	Pick-and-place task planned with the safe planner
RR-PF	Reach-and-retract task planned with the potential field planner
RR-S	Reach-and-retract task planned with the safe planner

Table III. CRS A460 dynamic limits.

Dynamic limit	Value
Velocity	3.14 rad/s
Acceleration	18.9 rad/s^2
Jerk	1000 rad/s^3

Given the path points generated for each task by the two planners, a motion trajectory was generated using a minimum-time cubic-trajectory planner planning in configuration space. For each path, trajectories at three different speeds were planned (slow, medium, and fast), resulting in 12 trajectories.

The trajectory planner generated a set of cubic path segments between each set of path points, resulting in a trapezoidal acceleration profile respecting velocity, acceleration, and jerk limits. The CRS A460-specified motion limits are given in Table III.

Each segment was described by a cubic polynomial, as shown here

$$Q(r) = b_0 + b_1 r + b_2 r^2 + b_3 r^3, \tag{6}$$

where r is the parameterized time, b_i are the cubic coefficients, and Q is the resulting joint trajectory.

$$r = kt \tag{7}$$

where t is the time and k is a constant scaling factor that

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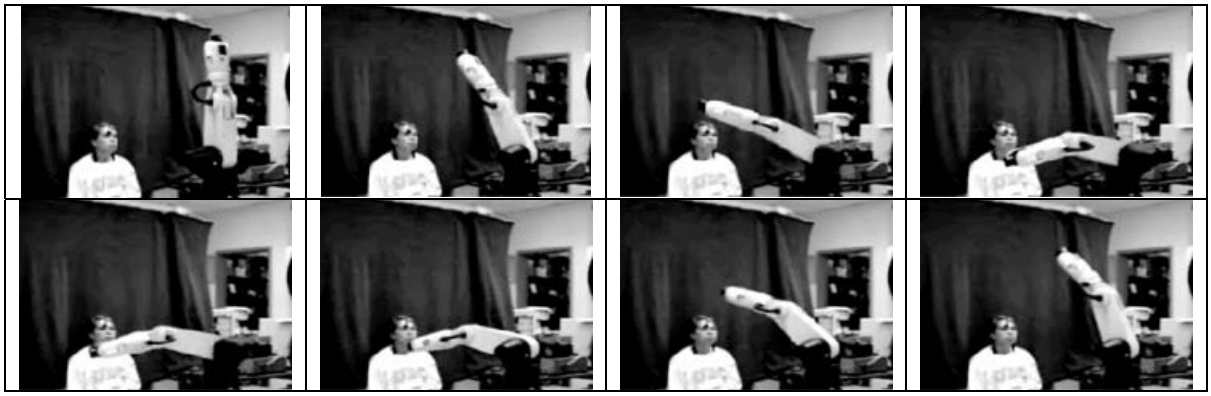


Fig. 5. Path PP-PF (pick-and-place task planned with the potential field planner).

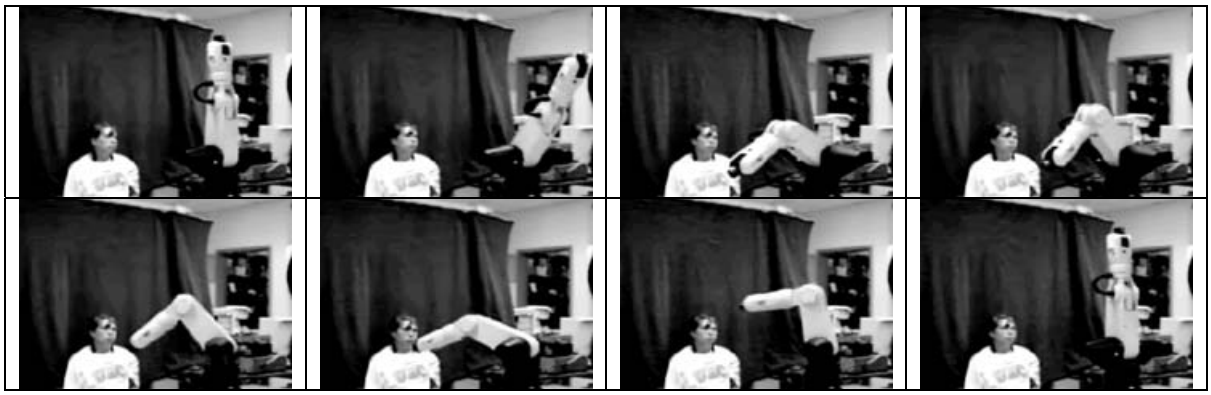


Fig. 6. Path PP-S (pick-and-place task planned with the safe planner).

scales the velocity, acceleration, and jerk on the trajectory. To generate the slow, medium, and fast trajectories, $k = 0.1, 0.5,$ and 1.0, respectively, were used. For both the tasks and both the planners, the robot comes to a stop in front of the person. The peak speeds along the path for both the planners are the same, but because of dynamic and kinematic constraints of the robot, the velocity along the path cannot be identical; however, the average speed along the path is within 10% for the two planners.

3.1.2. Physiological sensing. The ProComp Infinity system from Thought Technology[34] was used to gather the physiological data. This system has been used for several physiological studies in human–robot and human–computer interactions,[14,15,23] and is used by therapists for biofeedback applications.[34] As discussed in Section 2, heart muscle activity, skin conductance, and corrugator muscle activity were measured. The heart muscle activity was measured via ECG measurement using EKG Flex/Pro sensor. The skin



Fig. 7. Path RR-PF (reach-and-retract task planned with the potential field planner).



Fig. 8. Path RR-S (reach-and-retract task planned with the safe planner).

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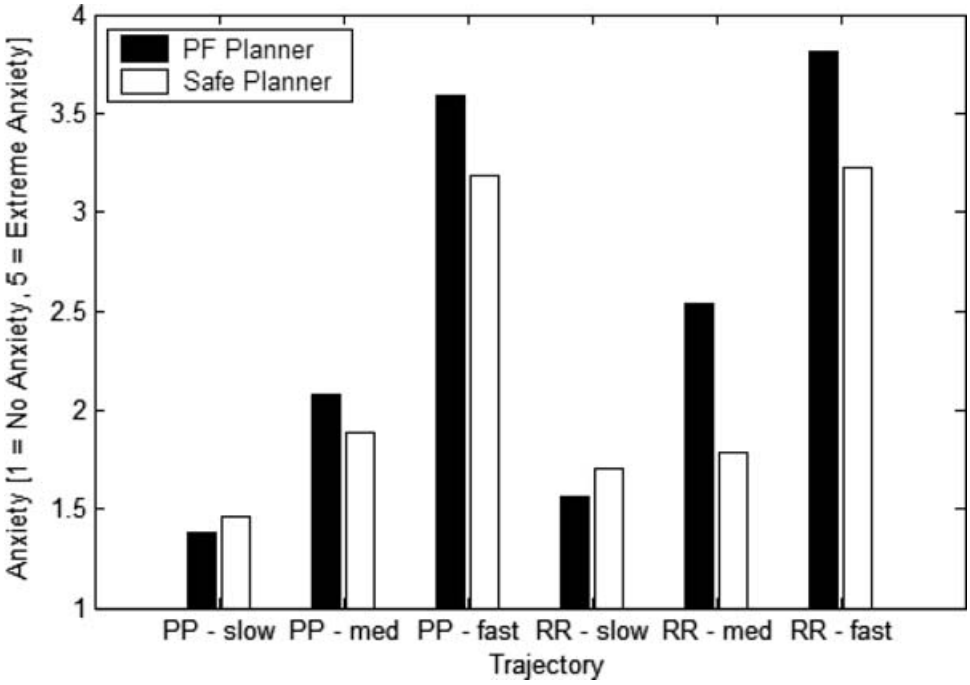


Fig. 9. Subject-reported average anxiety response.

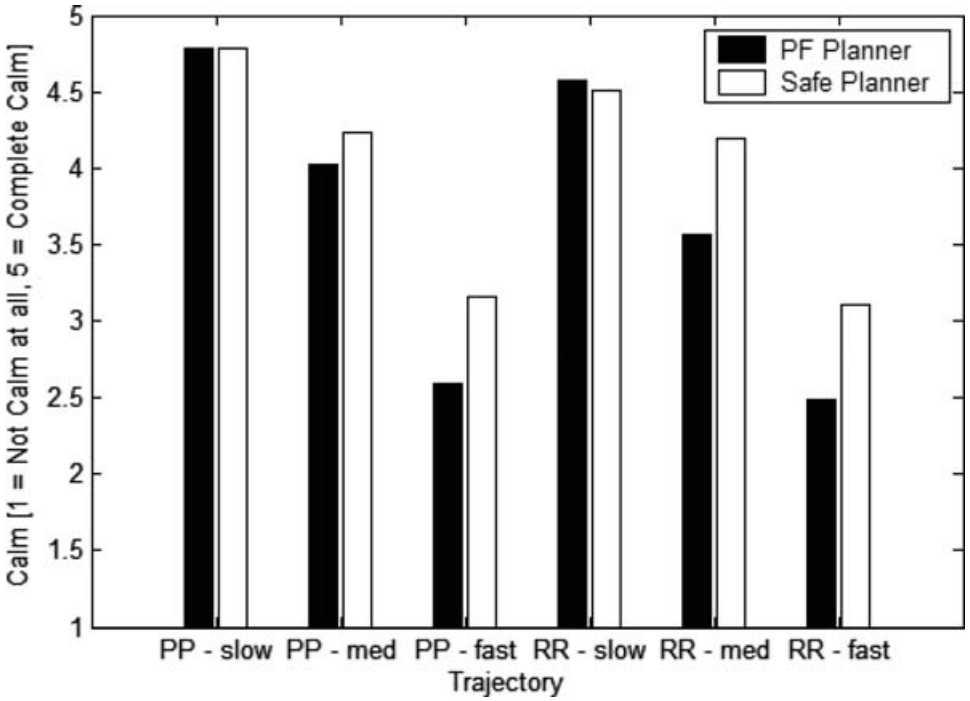


Fig. 10. Subject-reported average calm response.

conductance was measured using the SCFlex-Pro sensor. The corrugator muscle activity was measured with the Myoscan Pro electromyography (EMG) sensor. All sensor data were collected at 256 Hz. This rate is sufficient for capturing physiological signal events.

The robot controller and the physiological sensing computer were connected with a serial link. The robot controller would send a status indication at the start of each trajectory, so that the trajectory and physiological data could be synchronized.

3.1.3. Experimental procedure. For each experiment, the subject was asked to read a description of the experiment and sign a consent form. After signing the consent form, the experimental protocol was explained to the subject, and physiological sensors attached. The human subject was seated facing the robot. The robot was initially held motionless for a minimum of 90 s to collect baseline physiological data for each subject. The robot then executed the 12 trajectories described earlier. The trajectories were presented to each subject in a randomized order. After each

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trajectory had been executed, the subject was asked to rate their own response to the motion in the following affective response categories: anxiety, calm, and surprise. The Likert scale (from 1 to 5) was used to characterize the response, with 5 representing "extremely" or "completely," and 1 representing "not at all." The subject was also asked to rate whether the robot attracted and/or held their attention during the motion, on the same Likert scale, with 5 representing "full attention," and 1 representing "not attentive at all." The rating of each trajectory took approximately 30 s to complete. After the subjective response was collected, a 1-min rest period was enforced before presenting the next trajectory, to ensure that the physiological data could return to the baseline.

For each trajectory, the average arousal and valence over the duration of the trajectory were calculated from the physiological sensors data as processed by the inference engine described in Section 2.2.

4. Results

The data generated through the user study were analyzed in two stages. The subject-reported responses were analyzed to determine how the various robot motions affected the subject's perceived anxiety, calm, and surprise, and to determine if the safe planned motions were perceived to be less threatening. The estimated responses were analyzed to assess the effectiveness of the inference engine and the relationship between the physiological responses and the perceived affective state.

4.1. Subject–reported response

Figures 10–13 show the average subjective response and a comparison of the average responses between the potential field and the safe planned paths for the subject-ated anxiety, calm, surprise, and attention, respectively. Table IV shows the correlation analysis between the subjective responses and the speed for each trajectory type described in Section 3.1. For each set of variables, the probability value (p-value) was computed from a two-sided t-test. The p-value indicates the probability that the correlation was observed by chance. Due to the large sample size, the p-value for all correlations was less than 0.0001.

As expected, for each trajectory, there is a strong positive correlation between anxiety and speed, and surprise and speed, and a negative correlation between calm and speed. There is also a strong positive correlation between anxiety and surprise, and a strong negative correlation between anxiety and calm, and surprise and calm. Correlation among the subjective affective responses is shown to validate the use of the valence–arousal emotional model. There is also a weak correlation between the level of attention reported and the affective responses.

Table IV. Subjective results correlation analysis.

	Anxiety	Calm	Surprise	Attention	Speed
Anxiety	1.0000	−0.8174	0.7832	0.3760	0.6436
Calm		1.0000	−0.7119	−0.3258	−0.6413
Surprise			1.0000	0.3968	0.6843
Attention				1.0000	0.4476
Speed					1.0000

Table V. ANOVA for anxiety.

Significant factor	Sum sq.	DOF	Mean sq.	F	$p > F$
Plan	9.0422	1	9.0422	9.8287	0.001837
Speed	301.39	2	150.695	163.8018	0
Plan∗speed	7.5428	2	3.7714	4.0994	0.017241
Error	391.9132	426	0.91998		
Total	709.8883	431			

Table VI. ANOVA for surprise.

Significant factor	Sum sq.	DOF	Mean sq.	F	$p > F$
Plan	6.5023	1	6.5023	5.9369	0.015236
Speed	430.5104	2	215.2552	196.5382	0
Plan∗speed	8.4178	2	4.2089	3.8429	0.022177
Error	466.5694	426	1.0952		
Total	912	431			

A comparison of the graphs in Figs. 10–13 indicates that for each motion type (PP or RR), on an average the subjects reported lower levels of anxiety and surprise, and higher levels of calm, for the safe planned paths. This observation is confirmed by a three-factor analysis of variance (ANOVA) performed on the anxiety and surprise responses. The three factors are Plan [potential field (PF) versus safe plan (S)], Task (RR versus PP), and Speed. Statistically insignificant factors were removed and the data re-analyzed until only statistically significant factors remained.[35] The statistically significant factors at $p < 0.05$ for anxiety and surprise are shown in Tables V and VI, respectively. For these responses, the plan, speed, and plan∗speed interaction were found to be statistically significant factors. The task factor and all the task interaction factors were found to be statistically insignificant. A Levene test was performed, which confirmed the homogeneity of variances assumption at a significance level of 0.01%. For the subjective ratings (anxiety, calm, and surprise), the results show a statistically significant reduction in anxiety and surprise (and an increase in calm) when the safe planner is used, when compared with the generic potential field planner at medium and high speeds. The plan∗speed interaction indicates that at low speeds, the plan type does not affect the subjective response, while at higher speeds, the motion plan significantly affects the perceived anxiety, surprise, and calm. These relationships are found regardless of the type of task performed.

Table VII. Arousal ANOVA.

Significant factor	Sum sq.	DOF	Mean sq.	F	$p > F$
Task	0.03803	1	0.03803	13.57	0.0003
Plan	0.16803	1	0.16803	59.94	0
Speed	1.15162	2	0.57581	205.4	0
Plan∗speed	0.07712	2	0.03856	13.75	0
Error	1.19144	425	0.0028		
Total	2.6265	431			

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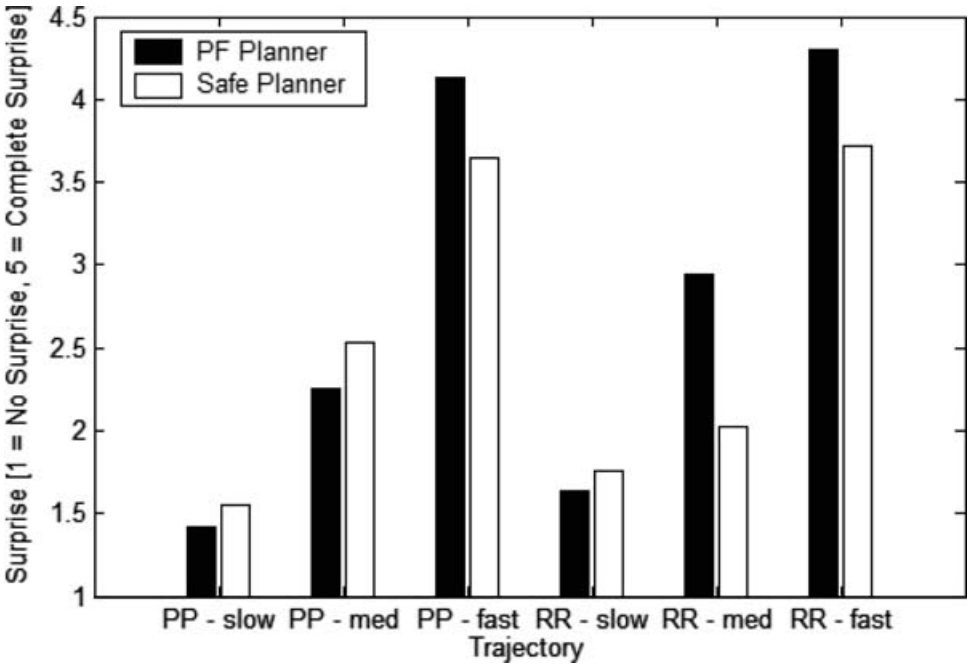


Fig. 11. Subject-reported average surprise response.

4.2. Estimated response from physiological sensors

4.2.1. Arousal. Figure 13 shows the average estimated arousal for each trajectory tested. The *y*-axis represents the level of arousal, which is output by the fuzzy inference engine as a normalized value in the range [0, 1], where 0 indicates no arousal, and 1 indicates highest arousal. Table VII shows the ANOVA for arousal, showing all significant factors at $p < 0.05$. A Levene test was performed, which confirmed the homogeneity of variances assumption at a significance level of 0.01%. As can be seen from the results, the estimated arousal behaves similarly to the subject-reported data. Estimated arousal tends to increase with speed, and this is the most significant factor in the ANOVA analysis. The plan type is the second most significant factor, showing that arousal is significantly lower when safe planned paths are used. Similar to the subjective response data, the plan∗speed interaction is also statistically significant. Unlike the subjective response data, for the estimated arousal, the

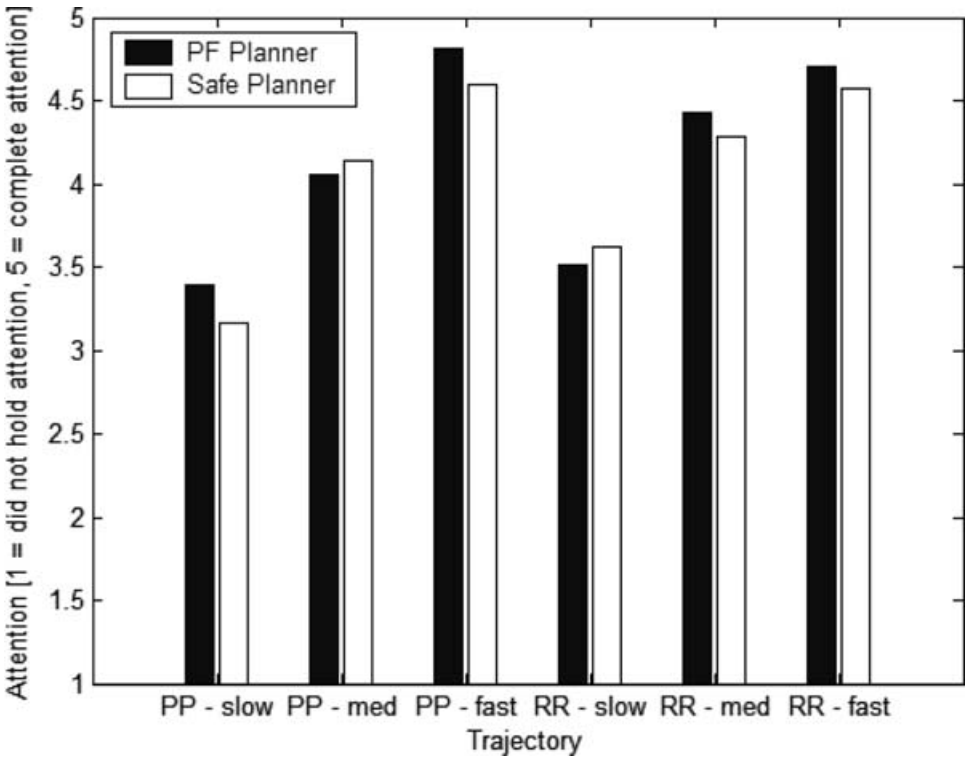


Fig. 12. Subject-reported average attention response.

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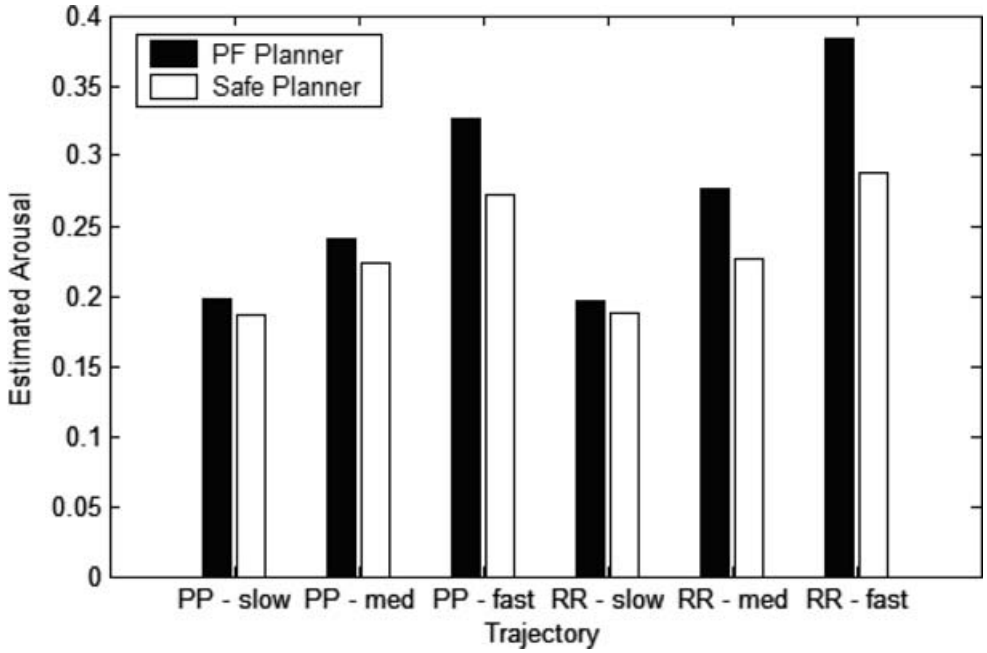


Fig. 13. Average estimated arousal from physiological sensors.

Table VIII. Correlation analysis for estimated arousal.

	Estimated arousal
Reported anxiety	0.5369
Reported calm	−0.5694
Reported surprise	0.5646
Reported attention	0.3766
Speed	0.6611

task type is also a significant factor, i.e., there is a significant difference in estimated arousal between the PP and RR tasks. Table VII shows the correlation analysis between the estimated arousal, the subject-reported responses, and the trajectory speed for each path. All of the correlations were found to be significant at $p < 0.001$. The estimated arousal is positively correlated with the reported anxiety and surprise, and negatively correlated with reported calm. The estimated arousal is also strongly correlated with the trajectory speed. However, unlike the subject-reported responses, the estimated arousal also has a small negative correlation ($r = -0.1334$, $p = 0.0055$) with the presentation order, i.e., trajectories presented toward the end of the trial tend to elicit less response than early trajectories, regardless of the trajectory type. This is due to the habituation properties of most of the physiological responses, especially the SCR.[20]

As described in Section 2, two signals were used for arousal estimation: SCR and heart rate. SCR is the more reliable indicator. SCR response to robot motions was observed for all subjects. Heart rate response was not as reliable, as only some of the subjects exhibited detectable heart rate response to robot motion stimuli. Ten of the 36 subjects exhibited heart rate deceleration following motion onset, consistent with the orienting response.[36] However, neither the magnitude of the deceleration nor the magnitude of the heart rate decrease varied with the type of stimulus. Therefore, heart rate deceleration appears to be more useful in detecting the presence of stimulus, rather than the severity of the stimulus. Only 3 of the 36 subjects exhibited heart rate acceleration in response to robot motions. For these subjects, the magnitude of the heart rate increase was correlated to the speed of the robot motion.

The fuzzy inference engine design addresses both HR responsive and nonresponsive subjects. Only very negative (VNEG) and very positive (VPOS) heart rate responses activate the rulebase; these types of responses are not observed for subjects who do not have a heart rate response to robot motion. Using only the extremum of the response also allows the inference engine to avoid false positives due to changes in heart rate correlated with breathing or slight posture changes.[19]

Table IX shows the confusion matrix for comparing subjective responses to estimated arousal. Estimated arousal was compared to the subjective responses by computing an estimate of the subjective arousal, based on the subject responses rating their anxiety, surprise, and calm. The subjective arousal was estimated as the maximum of the anxiety and surprise response and the inverse of the calm response

$$a_{\text{subjective}} = \max(S, A, 5 - C), \tag{8}$$

where $a_{\text{subjective}}$ is the subjective arousal, S is the reported

Table IX. Confusion matrix—Subject-reported vs. estimated arousal.

	Subject-reported arousal		
Estimated arousal	Low	Medium	High
Low	4	3	0
Medium	80	125	45
High	20	54	101

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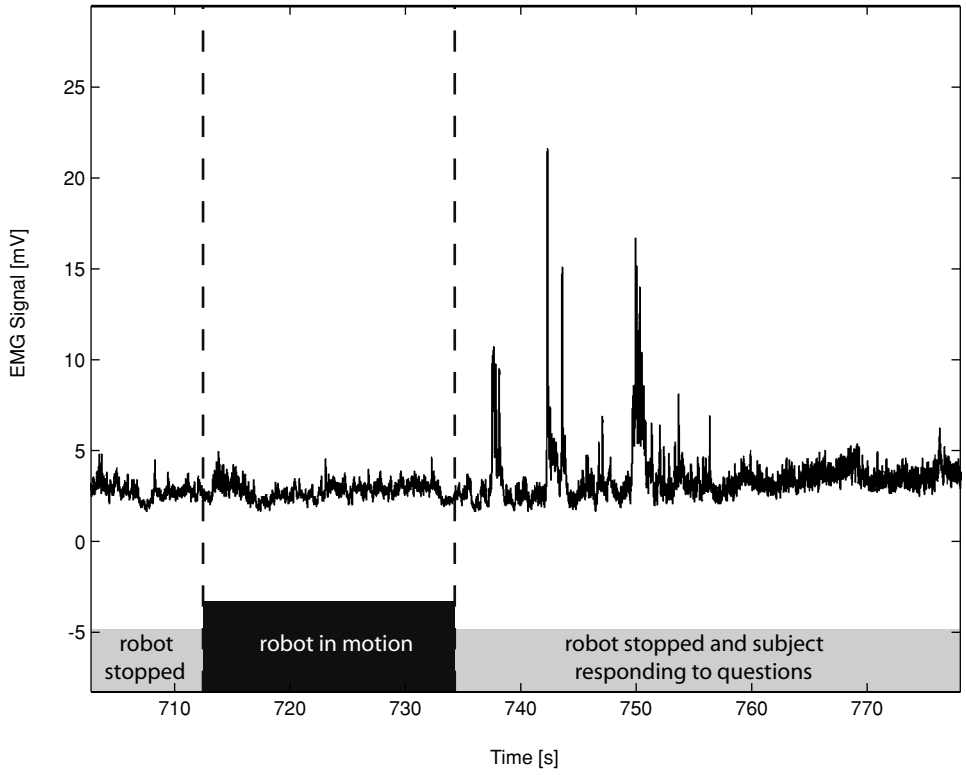


Fig. 14. EMG activity during question answering.

surprise, *A* is the reported anxiety, and *C* is the reported calm. For the subjective arousal, a response of 1 on the Likert scale was classified as low, a response of 2 or 3 was classified as medium, and a response of 4 or 5 was classified as high. As can be seen from the table, the inference engine performs better when the reported affective response is high. When subjects rated their anxiety or surprise as medium or high, estimated arousal was correctly classified as high 69% of the time. All of the misclassification of high subjective arousal was to the medium estimated arousal. That is, in no case was elevated arousal misclassified as low arousal. The inference engine is not effective in the low reported arousal region, where most of the responses are classified in the medium arousal range. The inference engine is far more likely to generate a false positive (high arousal when low surprise/anxiety are reported), rather than a false negative response. This is due to the fact that both heart rate and SCR response occur during the orienting response,[36] especially for novel stimuli. When subjects are presented with robot motion, some SCR response occurs even when they rate their anxiety and surprise as low.

4.2.2. Valence. The affective state inference engine also attempted to estimate valence, based on the corrugator muscle EMG signal and heart rate. As discussed in Section 4.2.1, only a minority of subjects exhibited heart rate responses to robot motions, so the heart rate was not a reliable indicator of valence.

The corrugator muscle activity has been reported to have a strong correlation with negative valence in existing studies,[15,23] and had shown promise during earlier studies with the inference engine using images as stimuli.[13] However, EMG activity was not reliably detected for the majority of subjects in response to the robot motion stimulus, confirming our earlier results.[17] Most of the subjects showed little variation of the EMG signal during robot motion. EMG activity was more likely to be observed following robot motion, while the subject was thinking about and announcing their subjective rating of the motion.

Figure 14 shows a common pattern of EMG response. During the robot motion, a very small change in EMG is observed; however, following the end of robot motion, while the subject is thinking about and articulating their subjective responses, significantly more EMG activity is observed. This result may indicate that corrugator EMG activity observed in earlier work using video game playing or picture viewing[13,15] is associated with cognitive processing, rather than instinctive response such as the startle reflex or fight-or-flight response. Further study to identify the physiological signals appropriate for valence estimation for this type of stimulus is required.

5. Conclusions

In this work, a set of physiological indicators and a fuzzy inference engine were proposed to classify human affective state in response to robot motion.

Two types of robot motions were presented to human subjects during the study: motions planned with a conventional potential field planner, and motions planned with the safe planner.[33] Subjects reported significantly less anxiety and surprise, and reported feeling more calm when safe planned motions were presented, as compared to the conventional potential field planner.

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The results from this study indicate that physiological signals provide a potentially useful additional signal for use during human–robot interaction. Fast robot motions tend to reliably elicit a strong, measurable arousal response. This information can potentially be used by the robot controller to reduce the robot velocity if a strong response is detected. For slow motions, a key question is whether the measured arousal indicates a measure of an involuntary reaction the subject may not be aware of (such as the startle reflex orienting response), or a measure of a consciously experienced affective state such as anxiety or surprise.

Corrugator activity does not appear to be a consistently measurable response to robot motion stimulus. Even when high levels of anxiety (a negative valence emotion) were reported, corrugator muscle activity was not reliably present, although it was commonly evident when subjects were performing a cognitive processing tasks immediately following the robot stimulus. This result identifies the need for further study to understand and interpret corrugator muscle response to various stimuli.

The affective state estimation using physiological signals presents a potentially valuable additional channel of communication for use in robot control, safety monitoring, and for improving the perceived safety of a human–robot interaction. This additional communication modality can be useful for improving the robot responsiveness to the human participant, especially in cases where other channels of communication may be unavailable, for example, in cases of disability. Continued work in this area is expected to lead to a more intuitive, better-perceived, and safer human–robot interaction.

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