Enhancing Collaborative Human-Robot Interaction Through Physiological-Signal Based Communication

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Abstract— **In order to develop a friendly and safe interaction between humans and robots, it is essential for the robot to evaluate users' affective states and respond accordingly. This paper investigates the use of physiological signals to estimate human affective states during a Human-Robot Interaction (HRI) task. We focus on characterizing physiological responses and understanding how affective states evolve in a collaborative human-robot task. We propose to both design a model that maps physiological signals to affective states in real time and design a methodology for the robot to exhibit an appropriate behavior during the task in response to estimated changes in affective states.**

I. Introduction

There has been a long standing interest in designing robotic systems to help people with their daily activities: completing chores, caring for the elderly, etc. Today, robots primarily are found in industrial settings - isolated from human workers - to automate tasks that are either too dangerous or that require a greater throughput or precision than a human worker can provide. Safe and robust human-robot interaction (HRI) in shared workspaces, however, has yet to be realized outside of the laboratory.

When people cooperate on a load-sharing task (*e.g*, carrying a table together) they use explicit and implicit cues to communicate with each other the actions they intend to take, their perception of task progress, and how the shared goal should be modified. A portion of interpersonal communication relies on implicit cues [4]. Furthermore, the communication/recognition of affective states is important to and expected by cooperating humans [5]. Therefore, robots intended to work with humans on shared tasks should be able to perceive their human partners' actions and intentions conveyed in both explicit and implicit modes. Additionally, a robot should use these modes to communicate its own plans and intentions. The ultimate goal of our research is to develop strategies for safe and intuitive interaction between humans and robots by enabling the robot to recognize affective state changes in its human partner and respond accordingly.

Several explicit and implicit cues can be used to estimate affective states in a partner, *e.g.*: characteristics of speech, facial expressions, gestures, postures, and physiological signals. This research will focus on the last of these cues to infer affective states during HRI. Physiological signals provide quantifiable measures that tend to be involuntary as well as age and culture independent.

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A. Specific Objectives

To study physiological-signal based implicit communication between robots and people, we will focus on the following four research objectives.

1) Characterize real-time human physiological responses elicited by the robot partner in an interactive task: The time and frequency domain physiological responses of the human in an HRI task will allow us to determine whether or not statistically significant changes in these parameters can be made online and if relevant features can be extracted from them in our HRI context.

2) Develop a model of the dynamics of the real-time evolution of affective states during a human-robot interaction task: While interacting with a robot, a person's affective state may change in response to different robot motions. We plan to study how these changes occur over time and which robotic stimuli elicit them.

3) Design a model to map physiological signals to affective states in real time: A sufficiently reliable model to map physiological responses to affective states would enable a robot to decode important implicit cues displayed by a human partner. Moreover, it will help validate the suitability of extracted physiological features while eliminating redundant or useless ones. Machine-learning techniques will be used to design such a model in real time.

4) Design a methodology for the robot to exhibit an appropriate behavior during a collaborative task: We will investigate appropriate responses of a robot to its human user in specific task-oriented scenarios in response to changes in the user's affective state. For example, should the robot alter its behavior if it infers a decrease in its user's affect, and if so, how? We will consider how responses should be defined and evaluated given a prescribed task context.

II. Literature Review

There is a rich body of psychophysiological literature related to affect estimation and the use of affect for Human-Computer and Human-Robot Interaction domains. However, very few studies have used the robot as the primary elicitor of physiological responses and changes in affect. Picard et al. [6] identified patterns in four physiological signals - electromyography (EMG), blood volume pressure, galvanic skin response (GSR) and respiration) - from an actor expressing eight different emotions, and were able to develop an emotion classifier that achieved 83% accuracy. Rani et al. [7], were able to recognize anxiety in five users based on several physiological signals (i.e., cardiac, electrodermal and electromyographic activity as well as temperature) using regression trees and fuzzy logic. Estimated affective states were compared to the subjects' self reports. Their earlier work was used to drive mobile robot behavior in simulated rescue domain [8].

Liu et al. [3], using a large set of physiological features and support vector machines, designed an affect recognition model achieving a success rate of 83% with children with autism spectrum disorders. Kulic and Croft [2] used Hidden Markov Models (HMM) to estimate affective state in response to various robot motions. Physiological signals including heart rate, GSR, and EMG. Offline questionnaires were used to assess users' affective states, represented using the valence-arousal model. User-specific HMMs successfully recognized valence and arousal better than 80% of the time.

III. Proposed Methodology

To achieve our first two specific objectives, we propose to perform a series of experimental trials in which a person and a robot perform a task together. The robot holds one end of an object with a pointing device attached (i.e., a laser pointer) and the person holds the other end. The human and the robot then trace a 2-dimensional path that has been drawn on a horizontal surface with the pointer. This task is analogous to many real-life scenarios: for example, in industry, a robot holds a heavy tool and the person guides the motion; in hospitals or care homes, for the elderly or patients who have diminished limb strength; in space station assembly as astronauts sometimes lose tools during repair missions. In all these tasks, the user decides when the task is done and the robot provides assistance for the task.

A CRS A460 robotic arm (human-sized) will be used with an ATI 6-axis force/torque sensor attached to the gripper. Robot behavior is set by an impedance controller (similar to that of [1]). During each trial the virtual impedance (i.e., mass and viscous damping), are changed randomly. The user is instructed to trace the path in each trial for one of the following two conditions: i) as fast as possible (speed), ii) as accurately as possible (accuracy). It is hypothesized that different values of the virtual parameters and/or random disturbances elicit changes in affect, as the task becomes easier or harder to perform. Throughout the experiment, several physiological signals are collected: i.e., electrocardiography, EMG, GSR, skin temperature, respiration rate and electroencephalography. After each trial, the user is asked to fill in a questionnaire to report their level of performance, effort, frustration, comfort, engagement, boredom and perceived helpfulness of the robot. Additionally, subjects will report their affective state based on video recordings of themselves during the trial.

To design a model to map physiological signals to affective states in real time (objective 3), a dynamic Bayesian inference network will be used. In this model, we will consider affective states as hidden variables and physiological signals as a high-dimensional vector of observations. We assume a first-order Markov process with observation variables depending only on the current hidden state. The parameters of the probability density function (pdf) of transition and observation are estimated using Maximum Likelihood. A recursive algorithm is used to make estimations in the Bayesian network [9].

Given affective state estimations, we will propose models of how the robot should respond (objective 4). The aim is to provide a decision-making process for the robot to appropriately adjust its behavior. Machine-learning algorithms for supervised learning will be investigated in this stage. These methods will be evaluated through user trials. It is expected that this will be an iterative process in which desirable behavior of the robot in response to estimated affect will be elucidated first from "Wizard of Oz" experiments. Outcomes of these trials will provide input to the decision making system that will then be evaluated in a series of trials to explore system effectiveness as well as the effect of the robot's failure to respond appropriately.

IV. Summary

In order to develop a comfortable and effective interaction between humans and robots, we focus on incorporating physiological measures as implicit cues for a robot to both recognize affective states in its human partner and behave appropriately. To this end, we focus on four specific objectives: 1) Characterize real-time human physiological responses elicited by the robot partner in an interactive task, 2) Understand the dynamics of the real-time evolution of affective states during a human-robot interaction task, 3) Design a model to map physiological signals to affective states in real time and 4) Design a methodology for the robot to exhibit an appropriate behavior during a collaborative task. This paper has presented a brief outline on how we propose to achieve these objectives.

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