Human-Robot Interactions Using Affective Computing

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Abstract

Affective human robot interaction (HRI) is quite complex since the robot interacts not only with the human but also with the environment. Providing robots with emotional intelligence is critical in this field but also achieving public acceptance and trust from the public when using robots is another challenge. Robots should infer and interpret human emotions and behave in a trusted way ensuring safety. Since affective HRI aims at the system development that use emotions, it requires knowledge from fields like computer science, psychology, and cognitive science. An affective autonomous robot interacts with humans using affective technologies to detect emotions. Despite the fact that a typical robot-platform has embedded several attributes like perception, decisions, and actions it is quite difficult to detect human emotions as well as to behave in a re-assuring manner.

Keywords

Human-robot interaction, affective computing, wireless sensor networks, EEG.

1. Introduction

The impact of affective computing and robots can be examined in the context of a smart house application. In a smart house [1] there is interaction with a wide variety of smart devices to robotic mechanisms. Such interactions have altered the objective of the house itself as a prime place to relax and unwind. Adding several smart devices inside our environment without any synchronization between them or planning regarding their integrated use can have a negative impact, manifested mainly as anxiety, stress and even insecurity. On the other hand, a properly scheduled and coordinated environment or, equivalently, a smart house ecosystem can significantly reduce stress and in general contribute to a higher quality of life. This happens only when the individual smart devices of a house ecosystem are working seamlessly and coordinated in the background taking into consideration the house occupants and not vice versa.

Among the major indicator of the well-being of human occupants of a smart house is that of calmness, defined as the state of mind having low arousal and valence [2]. Since calmness implies relatively low brain activity, it can be clearly identified using EEG [3, 4, 5] or through measurements related to ego-sensor data (smartwatch [6], smartphone [7]). A smart house seeks to provide an environment for increasing the calmness [8] by sensing several related intrinsic parameters (temperature [9], illumination [10], sound [11], et al.) and providing the necessary outputs (heating ventilation and air conditioning, light on/off state, loudspeaker music, et al.).

When it comes to affective computing considerations, the principal concern is for designing and building systems and environments where the HRI is smooth and human centered [12]. This includes building machines that can sense and react to human emotions but also to be reassuring, trusted and be considered safe by the public.

2. HRI: The case of a smart house

Our work presents the creation of an integrated environment that provides the foundation for a Smart house computing experimental platform. The experimental study enhances the frequent operations encountered in a smart house by monitoring its state using a wireless sensor network [13] and mobile robots [14]. This work describes the developed HRI testbed shown in Figure 1, indicating the following technologies that have been integrated to the Smart house platform:

- A Media Server attached to a dedicated computer (Intel i7-NUC).
- A supervising Data server (Intel i7-NUC) running Ubuntu 16.04 which infers the human's calm state based on a 10 second sliding window of EEG readings.
- The human brain activity is measured using an inexpensive yet reliable portable EEG-device. In this study the users' brain activity is used to validate the effect of various stimuli in a smart home towards the achieved calmness. An Emotiv EPOC+ EEG device [15] that transmits brain signals using Bluetooth to a computer is used. It can measure the brain waves of a human wearing the device and can transmit whether the user's emotion state.

CIKM'22: 31st ACM International Conference on Information and Knowledge Management, October 17–21, 2022, Atlanta, GA (companion volume).
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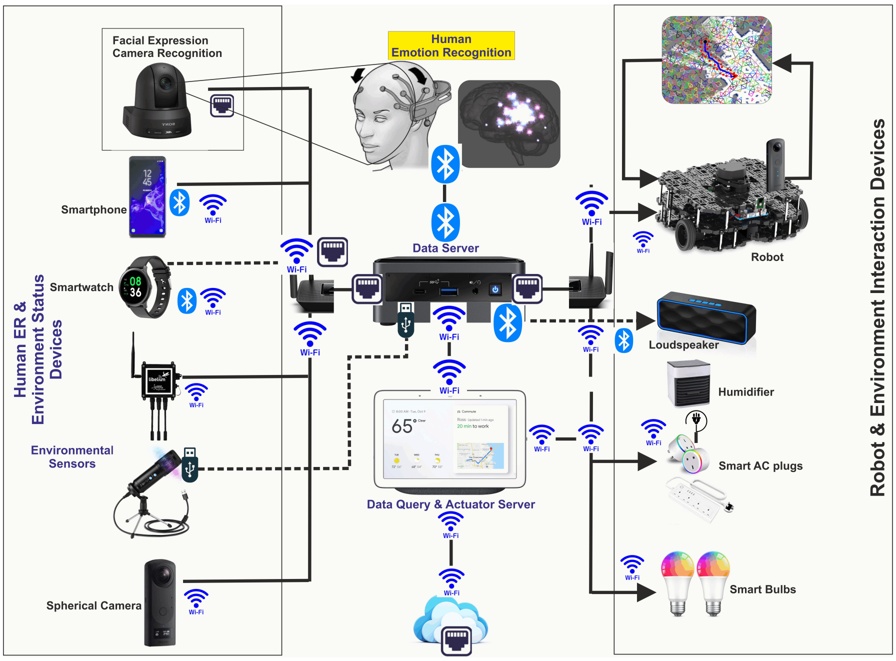

Figure 1: Human-robot interaction testbed.

- A suite of sensors that monitor the environment's status (sound, CO, humidity, temperature, et.al); these sensors are wirelessly connected to the supervised Data serer.

The utilized sensors include:

- A smartwatch (Samsung Galaxy Watch Active 2) running Tizen OS, which measures the heart rate of its user every 10 sec.
- An attention inference device in the form of an Android application running on a smartphone that detects the human's motion [1 bit word] and the call's state (Idle, Calling, Ringing) [2 bit word], every 5 seconds
- A smart house monitoring device (Libelium Waspmote and plug and play sensors) measuring: i) carbon monoxide (every 60 sec), ii) temperature (every 5 sec), iii) atmospheric pressure (every 5 sec), iv) humidity (every 5 sec), v) illuminance (every 5 sec), and vi) luminosity (every 5 sec).
- A sound sensor (microphone) connected to an Odroid XU-4 embedded microcontroller that monitors the power spectrum of the surrounding sound (over a 10 sec sliding window) and wirelessly transmits its normalized values [0 (noiseless) up to 1 (loud)] to the server,
- A spherical camera (Ricoh Theta V) that streams video at 4K-resolution to the data server; this camera is mounted on the mobile robot and monitors the surrounding space.

Moreover, a Google hub device acts as a data query and actuation server and sends event-like (on/off) commands to: a) a heat adjustment device (air cooler) for regulating the temperature, b) smart power outlets that connect WiFi RGB-light bulbs and other devices that affect the surrounding illuminance, and c) a Bluetooth-enabled loudspeaker device for playing streaming audio.

Finally, a mobile ground robot (Robotis' Turtlebot 3 [16]) controlled by an Intel i7 NUC with considerable number crunching capabilities. This computer is connected to the OpenCR (Cortex-M7) board and runs ROS [17]. This robot is equipped with a 360° line LiDAR that detects obstacles anywhere within 12-350 cm with a 1° angular resolution. This 2D-LiDAR is used for Hector SLAM [18] and obstacle avoidance. The mobile robot should not create additional attention while navigating its path within the smart house. For this reason, the robot should not be in the Field of View of the humans which is monitored by an IMU placed along the EEG-device.

3. Affective computing for robot applications

Humans living in an environment can perform perceptual, spatial, motor, and cognitive activities. In real life these activities are interleaved creating complex real life situations. We generated several scenarios that consist of different combinations of such activities, executed the scenarios in our smart house platform prototype and checked the human reaction using the EEG. Our initial results show that the user's emotions (calmness) are strongly influenced by the scheduling of the activities. More experiments need to be conducted to examine how user behaviour is influenced in different situations like simultaneous processing of clues, situations with low arousal and high arousal etc.

Several research directions can be followed based on the above platform. An interesting problem to examine is the use of AI based scheduler trained to the needs of the user. The problem of smart home scheduling has been examined mainly in the context of controlling appliances for efficient energy consumption [19].

Social robots, shown in Figure 2 have been used for a variety of applications. In [20], the major fields of applications for social robotics that include companionship, healthcare, education, are investigated. Furthermore, the incorporation of social attributes to the HRI under the social effects of these robots are highlighted.

For example in the education field social robots have been introduced for children education. In [21] social robots introduce a new perspective in understanding children learning. Robots are equipped with several sensors and data analysis of the collected data during their interaction with children can provide insights on the learning process. An interesting result on HRI in the case of children is presented in [22] where the authors use a NAO humanoid robot to a handwriting partner to teach children how to write.

In some cases the results of the use of social robots are not so encouraging. Such a case can be seen in [23] the authors examined the literature on using social robots for mental health interventions i.e. for improving depression and concluded that the research results have low internal and external validity. HRIs in social robotics can be remote or proximate. The problem of proximate interactions affects the Traits, Attitudes, Moods and Emotions (TAME) of humans. Examples of proximate activities between humans and robots can be as simple as the handover of an item or as complicated as a joint surgery. Human expectations and build of trust when considering robot errors is of paramount importance as explained in [24].

In our ongoing research, we are interested in proximate HRI [25], where humans interact with colocated robots. This interaction affects the sociability because of the robot's functionality. Proximate HRI includes social, emotive, and cognitive capabilities of this interaction.

The robot's architecture is modified to account for the underlying affective models. Inhere, the TAME framework [26, 27] is adopted to facilitate the overall HRI. Self

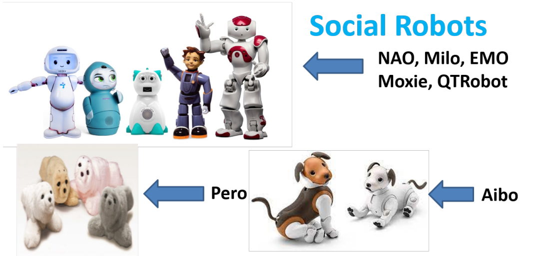

Figure 2: Commercial Social Robots.

assessments, or psychometric tests, or ongoing studies involving the Negative Attitudes toward Robots Scale (NARS) will be used to evaluate the HRI. Figure 3 indicates a mobile robot in our smart house that moves away from the human's Field of View in order not to affect NARS.

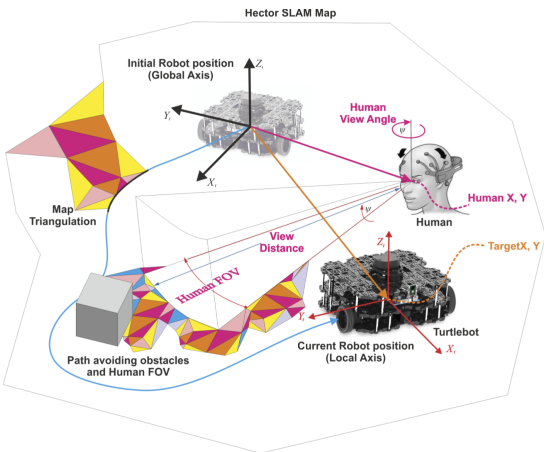

Figure 3: Robot's maneuver to decrease NARS

4. Conclusions

It is evident that in the field of HRI, there is a challenge that needs to be addressed on how to add characteristics and emotional intelligence to machines and environments so that the interactions with the humans to be intuitive, smooth, natural and trusted. This paper presented the development of a platform that encompasses several application fields and identifies future research issues related to machines, emotional intelligence and trust.

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