Designing Social Robots for Mental Heath Care

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***Abstract*— Mental health is a growing socio-economic burden worldwide and leads to negative ramifications including mortality and poor quality of life. Successful prevention, detection, and intervention of mental illness will make a significant, positive economic and societal impact. This research broadly explores how social robots may contribute to effective mental health care. In this work, we present our initial effort in designing and developing a social robot that detects emotional states through multimodal sensing of human behavior and provides affective companionship. We describe a pilot study exploring how people might interact with and perceive the robot. Our preliminary results show that participants treated the robot socially and engaged in affective interactions with the robot.**

I. INTRODUCTION

Mental health is a growing concern globally. Around 1-in-6 people in the world experience one or more mental illnesses [1]. The financial burden associated with mental illness is substantial and costs America approximately $193.2 billion per year [2]. Individuals living with mental illness face an increased risk of chronic medical conditions, increased risk of suicide, and involvement in anti-social activities. Despite being critical to overall well-being and physical health, diagnoses and treatment of mental illnesses remain low. Emerging research indicates that intervening early can interrupt the negative course of some mental illnesses and may, in some cases, lessen long-term disability [3].

As evidenced by successful applications in care for individuals with autism (e.g., [4]), Socially Assistive Robots (SARs) [5] represents a promising tool for mental health care. While prior research has explored how SARs might provide social, emotional support and companionship (e.g., [6]), this work investigates how a social robot may be used for early detection of mental health conditions. In particular, we leverage the embodiment and tangibility of a social robot and seek to infer a person's psychological states through multimodal sensing of human behavior, including auditory, visual, and haptic cues. Affective touch is a crucial element of social bonding and for affective communication and provides rich information for understanding a person's emotional state. We envision that such a social robot will help identify the unobserved psychological stressors to better inform therapy.

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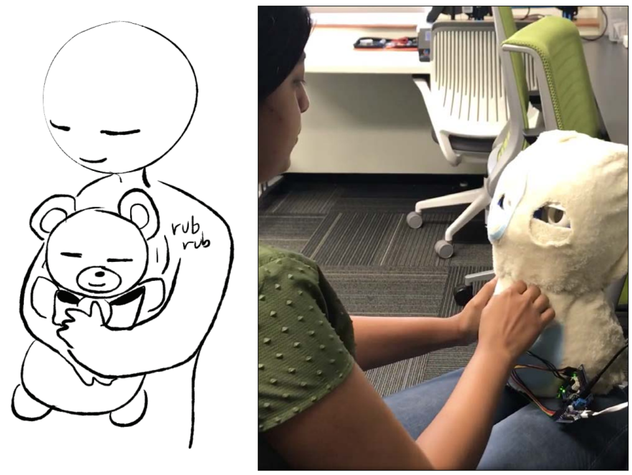

Fig. 1. Left: Our social robot is designed to afford affective interactions through touch, hug, and other haptic gestures. Right: Our prototype robot responds socially through nonverbal behaviors based on detected human interaction behaviors.

II. ROBOT DESIGN

The physical dimensions of the robot are 17x15x30 centimeters and weighs about 2.36 lbs. The robot has 6 DOF, eye-lids open and closing mechanism (2 DOF), eyeballs pan and tilt mechanism (2 DOF), and neck rotation mechanism (2 DOF). The entire robot is covered with artificial fur to encourage the users to make physical contact with the robot. It is equipped with a camera, a microphone, an IMU, and tactile sensors.

The robot consists of several software modules that sense, interpret, and respond to human behaviors. The gesture recognition module makes use of the contact information obtained from the tactile sensors that cover the robot to classify the haptic contact into a gesture. The gestures that the robot can recognize include stroke, contact, hug, hold, rub, pat, and squeeze. In addition, the IMU data is analyzed to infer the robot's posture such as toss, rock, and lift.

The face tracking module utilizes the Single Short Multi-Box detector (SSD) for face detection and seeks to maintain the detected face at the centre of robot's visual field. The emotion recognition module takes the sensor (camera, microphone, and tactile) inputs and interprets the emotional state of the user. In particular, visual emotion is recognized using the mini-Xception network, while auditory emotion is obtained from a train DNN network. The details of the design of the robot are documented in [7].

The robot is designed to respond nonverbally to human interactions. Its nonverbal responses are generated through two layers: a behavior-planning layer and a behavior gen-

Fig. 2. Interaction examples from our pilot study. The participant engaged with the robot through various forms of affective touch.

eration layer. The robot's behavior is based on its internal states, which is influenced by the user's inferred emotions. The behavior-planning layer takes input from the modules of face tracking and emotion detections to determine the robot's internal state. This layer then decides a particular response from a pool of predefined responses and sends basic behavioral patterns to the behavior-generation layer. The behavior-generation layer generates control references for each actuator in order to perform the behavior coherently. The behavior-generation layer adjusts the priority of behaviors based on the robot's internal states. This design creates lifelike behavior for affective interactions.

III. A PILOT EXPERIMENT

We conducted a pilot, exploratory study to explore how people might interact and perceive our designed robot. Two female participants were involved in this study. During the study, artificial emotions including anger, neutral, happy, fear, amusement, and sadness were simulated and the interaction between the robot and user under different emotions was observed. The emotions were stimulated by viewing a video for 22 minutes which was created using the Ravdness and International Affect Picture System datasets [8].

A. *Preliminary Results*

The participants were excited to meet the robot and greeted it friendly during the introduction. We observed that the participants interacted with the robot willingly from the beginning and throughout the session. They spoke to it, and stroked and hugged it. During the study, the participants held the robot on their lap when watching the video and patted it from time to time. We observed that participants held the robot facing outward to the presented video stimuli for most parts of the experiment. However, the participants turned the robot to face themselves at points when they wanted to talk to the robot or were "checking on" the robot as if they were making sure the robot was not having a dramatic experience. Fig. 2 shows some sample interactions between a participant and the prototype robot.

IV. FUTURE WORK AND CONCLUSION

We envision that social robots will soon be capable of providing social, emotional support and companionship to a diverse groups of people and can serve a unique role that augments human specialists in mental health care. As an initial effort, this work explores the design, development, and evaluation of a social robot for affective interactions with people. We are particularly focused on interactions through affective touch, as it provides rich information about human emotion that complements common visual and auditory cues. While still in its early stage, this work highlights promising opportunities that social robots may offer for mental health care regarding prevention, early detection, and behavioral intervention.

Moving forward, we will integrate feedback from our pilot study into and iterate the design and development of our social robot. We aim to conduct a field study to investigate how people might interact with the robot in their environments and more broadly explore the possibilities and limitations of social robots for close, affective interactions. Ultimately, we will work toward integrating social robots into mental health care.

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