Robot Sensor Data as a Means to Measure Human Reactions to an Interaction

Wilma Bainbridge, Shunichi Nozawa, Ryohei Ueda, Kei Okada, Masayuki Inaba
The JSK Robotics Laboratory
Department of Mechano-Informatics, The University of Tokyo
Tokyo, Japan
wilma.bainbridge@gmail.com

***Abstract*—This study investigates a methodology using sensor data from a humanoid robot to interpret a human's feelings towards a social interaction with the robot. Subjects of diverse backgrounds taught the robot how to play a rock-paper-scissors game while the robot discreetly took measures of hand temperature, tactile pressure, forces, and face distance. Before and after the interaction, surveys were administered to measure the subject's technophobia level and reactions to the robot. Several correlations were found between the questionnaire data and sensor data, following tendencies supported by previous research and psychological studies. The usage of robot sensor data may provide a quick, natural, and discreet alternative to survey data to analyze user feelings towards a social interaction with a humanoid robot. These results may also guide roboticists on the design of humanoid robots and sensors able to measure and react to their users.**

Sensor data; biosignal data; technophobia; human-humanoid interaction; human-robot interaction; handshake

I. Introduction

When we meet someone for the first time, the initial handshake leaves a strong first impression. A firm, warm handshake will create a better rapport than a cold, weak one. We constantly use measures such as temperature, sweat, and eye contact to assess what another person is feeling, and then dynamically adapt to that person's stress level. However, in human-robot social interaction, researchers often depend on more explicit measures rather than signals of a person's internal state.

Within the field of human-robot interaction (HRI), surveys are the most common way to receive feedback about the user's experience. While surveys do collect clear opinions, filling out a survey can be unnatural and lengthy for a subject. Surveys can be affected by response bias, where subjects select answers based on perception of the questionnaire rather than the questionnaire content itself [1], and surveys are also cumbersome for researchers to prepare, transcribe, and analyze. For quick, natural-environment, or multi-user experiments, it may even be impossible to administer a survey.

A segment of HRI research is beginning to focus on interpreting a user's reactions to a humanoid robot through non-survey techniques. These techniques include behavioral analysis [2], speech analysis [3], and external biofeedback device usage [4]. Our research wishes to use the variety of sensor data that is collected by a robot during an interaction, including temperature, forces, and face distance. These sensor data may be usable as biosignal data that reflect objective readings of a subject's feelings towards a robot. In psychology research, biosignal data – particularly hand temperature - have been frequently used to measure stress and relaxation [5,6,7]. This study combines this long-used psychological methodology and the well-developed sensing abilities of humanoid robots to create a tool for HRI research.

The usage of sensor data presents many benefits over survey data. First of all, the data can be collected in large amounts – for example, in this study, at the rate of about 1700 measurements per minute for each sensor – allowing experimenters to analyze small changes over time. There is also a wide variety of small sensors available that can be attached to a robot to adapt to different types of interactions. This experiment utilizes temperature sensors, tactile sensors, and cameras, but one could also imagine including sensors like skin conductance sensors or heart rate sensors. Most importantly, the usage of sensors attached only to the robot creates a natural environment. The sensors can be unnoticeable, and there is no preparation needed for the human subject. When using a humanoid robot, the data collection becomes very natural – the humanoid robot only has to shake hands with a person to establish contact and collect data on their feelings, just as humans regularly do in their own handshakes.

In order to establish the effectiveness of this methodology, one main measure we use for comparison with the sensor data is the level of technophobia a subject has prior to the experiment. Technophobia is a phenomenon that occurs when people feel a resistance and anxiety towards emerging technologies [8]. For example, people who refuse to upgrade from VCRs to DVRs out of fear of acclimating to a digital format can be considered "technophobes". HRI research has used survey measures of technophobia in order to analyze interactions [9]. Technophobia may play a strong role in how relaxed and positive people feel when interacting with humanoids, and would be the clearest measure for assessing the accuracy of sensor data.

Previous studies we have conducted have found strong correlations between a person's behaviors towards a robot (such as reciprocation, vocalizations, etc) and the sensor data a robot collects [10, 11]. This study looks at the more explicit measures of survey data and analyzes their correlations with sensor data. While our past studies have been in fast-paced, multi-user environments, this study takes place in a one-on-one, focused teaching environment, allowing us to analyze change in an individual subject's data over time. We also explore which sensors are particularly relevant for HRI research.

II. METHODOLOGY

A. Overview

Human subjects were asked to teach the robot how to play the game "rock-paper-scissors" and then play it with the robot. Subjects taught the robot by physically moving its right arm and fingers. This task was chosen for several reasons: it is internationally well-known, it involves continuous touching of the robot's hands, it can be easily and safely performed by a three-fingered humanoid (versus an interaction that requires complex body movement), and the arm position is the same for each move, so a repeated measure for a constant gesture can be taken. The "game" element and allowing the subject to see actions they taught to the robot makes the experiment also more rewarding and meaningful for the subject. Fig. 1 shows example hand positions for the robot for each game gesture. The robot also shook hands with the subject before and after the interaction to take extra sensor data measurements.

B. The Humanoid Robot HRP-2

This study uses the humanoid robot HRP-2, developed by Kawada Industries. The HRP-2 is a bipedal robot weighing 58 kg, measuring 154 cm tall, and is equipped with 30 degrees of freedom (DOF). Our laboratory has replaced both of the HRP-2's hands so that they include three fingers each, with 2 DOF in the thumb, 3 DOF in the index finger, and 1 DOF in the middle finger region. We added several sensors to the robot's hands for the purpose of this experiment: eight tactile sensors (Interlink Standard 400 force sensing resistors; three each on the thumb and index finger, two on the index finger), and three temperature sensors (SEMITEC extra-thin high-precision thermistors; one each on the robot's palm, thumb, and index finger). These sensors are covered and are not noticeable to the subject.

In order to make a realistic interaction, we gave the HRP-2 speech synthesis abilities, using AquesTalk [12] for Japanese speech and Festival [13] for English speech. The robot was given a "cute," robotic female voice, which was selected for the robot through a general campus survey [10].

The robot's program was written in Euslisp [14], using a ROS architecture [15] that allowed for asynchronous control of the robot's head and body. The robot's head faced the subject when shaking hands, confirming the taught gestures, and when playing the game. The robot's head followed its own hand when the subject was teaching the robot gestures.

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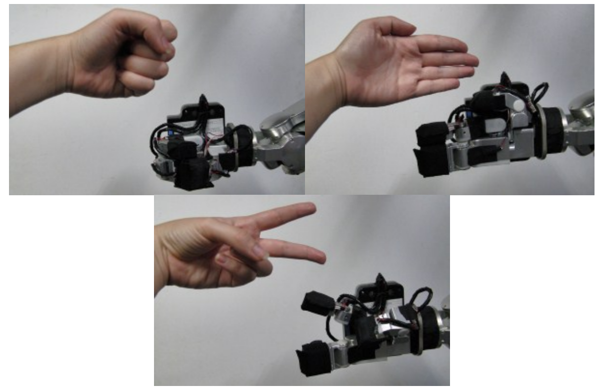

Figure 1. Example rock-paper-scissors gestures between the HRP-2 and a human (upper left: rock; upper right: paper; bottom: scissors)

C. Participants

Thirty-eight right-handed subjects were recruited for this study. Subjects ranged in age from 19 years to 33 years, with an average age of 23 years. Fourteen subjects were female, while 24 were male. Subjects came from diverse backgrounds, including 12 different universities and companies in Japan, 15 different fields (engineering, economics, theatre, etc), and 14 different countries within North America, Europe, and Asia. This study was run in either Japanese or English, based on the language most natural for each participant. The language choice affected both the language in which the robot spoke and the language of the questionnaires. The same experimenter wrote both languages' scripts and surveys, ensuring translation accuracy.

D. The Interaction

Refer to Fig. 2 for images depicting the main steps in the interaction. Subjects were first asked to answer a survey measuring technophobia before seeing the robot, although they were not told the topic of the survey so as to diminish response bias. This survey included parts of the Technophobia Measurement Instrument, developed by Weil et. al [16], which includes three main components: "the computer anxiety rating scale," "the computer thoughts survey", and "the general attitudes towards computers scale." We added a fourth section that asked similar questions to the "general attitudes towards computer scale", but were related to humanoid robots instead of computers. Subjects' hand temperatures were also taken from the palm and back of the right hand before seeing the robot to serve as a baseline for the study.

The experimenter then described the study and showed a demonstration video of the interaction with the robot. Subjects were told that they were going to teach the robot how to play rock-paper-scissors, and then they were going to play the game with the robot five times. The subject then got to meet the robot. When the subject stood in front of the robot, the robot tracked the subject's face, moving its head to make "eye contact" with the subject. After tracking the subject's face for five frames, the robot initiated a handshake, waited for the subject to grab its hand, and then shook it carefully.

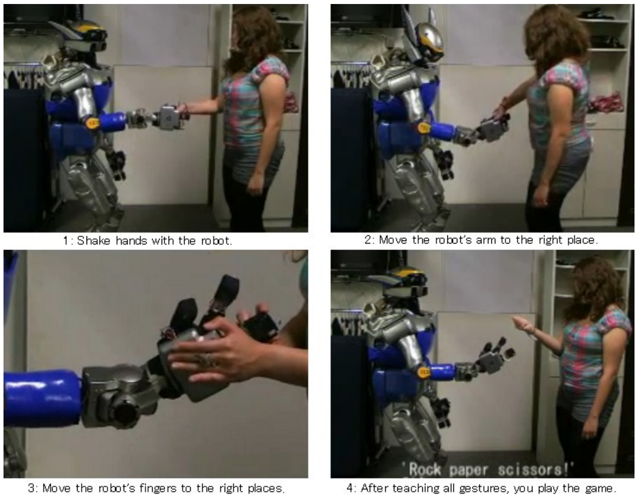

Figure 2. Images from an example interaction with the robot.

After the initial greeting, the robot went into "learning mode," where the subject taught the robot how to make the gestures for rock-paper-scissors. The subject took the robot's hand and the robot grasped it in a manner similar to a handshake. Then, the subject moved the robot's arm to the right position for a gesture. The subject then pushed down on the robot's shoulders to "save" that position and the robot released the subject's hand. The subject then moved the robot's fingers into the right positions and then press down on the shoulders again to save the finger positions. The robot confirmed that gesture by showing the subject what it was taught. The subject was asked to teach the robot six times total – teaching each gesture (rock, paper, scissors) twice. The ordering of the gestures was randomized for each subject.

After the teaching period, the subject played rock-paper-scissors with the robot five times. For each move, the robot randomly selected one of the gestures taught to it by the subject. After each throw, the robot reacted vocally to whether it won, lost, or tied each game. The experimenter covertly inputted the subject's move to the robot, so that the robot would seem to be reacting naturally and accurately to the game.

After the game, the subject shook hands with the robot one last time as it said goodbye, and then subjects were asked to fill out a post-experiment survey. This survey included biographical questions (age, gender, nationality, etc), questions about the robot's personality (what adjectives people would assign to it, whether it was scary, etc), and questions about the interaction itself (whether it felt meaningful, what suggestions they had, etc).

The interaction with the robot took approximately twenty minutes, and the entire study took about forty minutes per subject. During the interaction, the experimenter sat out of view from the subject, but was accessible if the subject had questions or felt uneasy. When asked questions, the experimenter either repeated the instructions, repeated what the robot said, or stated, "I'll explain in detail after the experiment." The rooms used in the experiment were kept at the same basic temperatures across the span of the study.

E. Data Collection and Analysis

During the experiment, the robot was constantly taking sensor data from the subject. With its cameras, it recorded the subject's face distance from the robot using a face-detection software plugin. With its hand, the robot took the subject's hand temperature (three places as described in Section II-B) and tactile pressure (eight places). The robot also measured the force on the joints in its arm in six directions (x, y, z, roll, pitch, yaw). A linear regression analysis was also run for each subject on all temperature data measurements over the time of the experiment, and slope of the regression line and correlation coefficient r were used as two additional variables to examine in comparison to the survey data. These variables will be referred to as the six measures of temperature growth, corresponding to a slope and a correlation coefficient for each of the three temperature sensors.

Each subject's data totaled over 30GB, so the data were put through many filters to get them to a manageable size. Biographical and survey data were combined with the sensor data by subject. Four subjects' data were discarded because of network or disk space errors that prevented most of their sensor data from being saved. This study focuses on the data during the experiment beginning and ending handshakes and the moving of the robot's arm during teaching, because these behaviors present the most consistent movement. The moving of the robot's fingers included a wide diversity of actions (for example, the many ways to represent "scissors"), and there was little contact with the robot's sensors, so those data were not analyzed. The dataset for each subject's first taught gesture was also counted as a "test phase" and thrown out, since subjects used the first gesture to learn the pacing of the experiment and to ask the experimenter questions about how to teach the robot.

Data amounts were normalized across subjects by action, so that subjects who took longer during interaction with the robot did not have more influence over the data. Data normalization involved finding the minimum number of sets of data within an action, a set being defined as the collection of measurements from all sensors at each time point for a given subject. Then, a random sample of that number of sets was taken from each subject's data. In the end, 312 sets per subject were used for the first handshake, 511 sets were used for the holding of the robot's hand when beginning teaching, 3037 sets were used for moving the robot's arm across the five teaching phases, and 269 sets were used for the final handshake. In total, 4129 sets were used for 33 subjects, while 3860 sets were used for one subject, whose data were missing one gesture's teaching due to a network error. In total, 140,388 sets of data were analyzed.

III. RESULTS

We conducted Pearson's correlations across the sensor data and questionnaire data. A color-coded chart of correlations reported in this section can be seen in Fig. 3. Some questionnaire items had no significant correlations with the sensor data, and were not included here. Measures were only included in this analysis when all three temperature measures had significant correlations in the same direction. Correlations between survey items were not investigated unless if related in

	Temperature			Temperature Growth						Face Distance	Tactile							
Low vs. **high** technophobia	+ .215	+ .109	+ .140	+ .034	– .066	– .135	– .164	+ .118	+ .153	+ .294	– .029	+ .066	+ .036	+ .007§	– .040	+ .025	+ .019	– .062
Younger vs. **older** age	+ .096	+ .189	+ .115	+ .237	+ .225	+ .254	+ .198	/ .003	+ .153	+ .120	– .018	+ .079	+ .059	+ .012	– .019	+ .105	– .100	– .079
Other major vs. **engineering major**	+ .072	+ .169	+ .145	+ .530	+ .525	+ .627	+ .437	+ .217	/ .000	+ .015	+ .041	– .036	– .034	+ .019	+ .016	– .140	– .079	– .056
"Not scary" vs. **"scary"**	+ .254	+ .188	+ .061	+ .025	+ .048	– .077	– .010	+ .034	+ .066	+ .055	– .009Ø	+ .039	+ .006*	+ .008Ø	+ .017	– .063	– .015	– .060
"Meaningful" vs. **"meaningless"**	+ .006*	+ .113	+ .133	+ .134	+ .149	+ .222	+ .309	+ .014	/ .003	– .129	– .047	+ .089	+ .044	+ .005	– .032	– .054	+ .017	+ .045
Positive vs. **negative** response to touch	+ .093	+ .050	+ .170	– .167	– .224	– .262	– .192	+ .107	+ .211	/ .002	+ .038	+ .100	+ .018	+ .011	+ .014	/ .002	+ .038	+ .034

Figure 3. A chart indicating statistically significant correlations between questionnaire data and sensor data. Each cell represents the set of correlations between its corresponding column header and row header. Temperature, temperature growth, and tactile readings had multiple measures, so they are reported here in order of their sensor number (as described in Section III). The numbers within each cell indicate the correlation coefficients for each measure, while the symbol above each number indicates the direction of the correlation (+ is positive, / is no significant correlation, and – is negative). The colors of the cells correspond to amount of agreement of correlation direction across measures; darker colors mean stronger sensor agreement, while lighter colors mean weaker sensor agreement. Blue indicates sensor agreement towards a positive correlation, white indicates no sensor agreement or no significant correlations, and red indicates sensor agreement towards a negative correlation. All of the above correlations have a significance of $p < 0.001$, except for those marked after the correlation coefficient with Ø ($p < 0.005$), § ($p < 0.01$), and * ($p < 0.05$).

content to sensor correlations, as solely survey-based analysis was not the focus of this study.

First, we compared the sensor data for subjects' handshakes at the beginning and end of the interaction, through an independent samples t-test. While tactile and face distance measurements did not show any significant change, hand temperatures were significantly higher during the latter handshake than the former one (*robot palm thermistor:* $t(19463) = 36.203$, $p<0.001$; *thumb thermistor:* $t(19463) = 19.790$, $p<0.001$; *index finger thermistor:* $t(19463) = 20.367$, $p<0.001$).

We then looked at correlations in the data, first looking at correlations related to the technophobia questionnaire administered before the experiment. Lower levels of technophobia were correlated with higher hand temperatures, farther face distances, and higher tactile readings from five of the eight sensors. Looking at post-experiment survey items related to technophobia, there was a correlation between lower technophobia and younger age ($r=0.349$, $p<0.001$), as well as lower technophobia and more engineering experience ($r=0.090$, $p<0.001$). Following a similar trend as technophobia, subjects of younger age tended to have higher temperatures and farther face distances. They also tended to have higher growth in their temperatures over the course of the experiment, in five out of six of the measures of temperature growth. Interestingly, while majoring in engineering was correlated with a lower level of technophobia, subjects who did not major in engineering tended to more closely match the pattern of sensor data linked with low technophobia: higher temperatures, higher temperature growth over time in five measures, and farther face distances. However, like those with technophobia, non-engineers had lower tactile measurements from five out of eight of the sensors.

We then looked at correlations between the sensor data and the post-questionnaire. Subjects who rated the robot higher as being "not scary" (versus "scary") tended to have higher temperatures, farther face distances, and higher temperature growth on four measures. Subjects who rated the interaction with the robot as feeling "meaningful" (versus "meaningless") also had higher temperatures and higher temperature growth on five measures, but had closer face distances. In the open-ended portion of the post-questionnaire, subjects were asked, "How did touching the robot affect your feelings towards it?" The responses were coded blindly for being positive, neutral, or negative. From this coding, there was a significant correlation between people who gave more positive responses and higher temperatures and higher tactile readings on seven measures. However, there was also less temperature growth for these subjects in four measures.

IV. Discussion

Hand temperature stood out as the sensor measurement with the clearest tendencies. As expected, hand temperature tended to increase across the experiment, and was greater during the last handshake than the first one. This is likely due to a natural warming up from using one's hands, but could also indicate "warming up to," or feeling closer with, the robot over time. Across all measures, hand temperature was most closely linked to the survey data, with positive feelings such as enjoying contact with the robot or finding the robot not scary resulting in higher temperatures, while negative emotions such as technophobia or finding the experiment meaningless were linked with lower temperatures. This overall pattern of warmer temperatures reflecting positive feelings in an interaction follows the same pattern found in a separate study linking sensor data to behavioral data [11], and has been supported by psychology research [6,7]. Younger age was also linked to lower technophobia and higher temperature. Interestingly, engineers tended to have lower hand temperatures versus non-engineers during the interaction. This could be the result of having too much knowledge that may "demystify" and "objectify" the robot. People with too much engineering background may know too well how the robot is working, and interact with it as a toy rather than as a social partner. A similar pattern of engineering background resulting in negative sensor data tendencies has been found in our previous research [11]. There were also correlations in the post-questionnaire that seemed to reflect engineers' objectification of the robot. In the post-questionnaire, subjects were asked to give the robot a name, which were then blindly coded by the experimenter as being a human name (for example "Timmy") or a robotic name (for example "Robocop"). Subjects with an engineering background were significantly less likely to give the robot a human name ($t(140095)=79.85$, $p<0.001$). They also rated the robot as more "machine-like" than "human-like" versus their non-engineering counterparts ($t(140095)=85.66$, $p<0.001$).

Along with temperature, there were also strong correlations related to the temperatures' changes over time. In general, there were the same positive tendencies: finding the robot "not scary," finding the interaction "meaningful," a non-engineering background, and younger age were correlated with higher temperature growth over time. Being a non-engineer had an especially high correlation with temperature growth, possibly indicating drastic "warming up" to a technology that they were initially inexperienced with. Surprisingly, feeling a positive reaction to touching the robot had an opposite tendency, and was correlated with lower temperature growth. This could have resulted from a number of possible explanations. These subjects who had a positive reaction to touching the robot tended to have higher starting hand temperatures before the experiment (*palm:* $r=0.102$, $p<0.001$; *back:* $r=0.144$, $p<0.001$). Their starting temperatures could have been higher because of initial positive feelings towards the experiment, or perhaps a generally relaxed state. This also means that there was less room for temperature growth, compared with the subjects with the negative reaction to the robot's touch. However, the lower temperature growth could also be caused by these subjects quickly acclimating to the robot's touch, or a data-related cause (as only four out of six measures indicated lower growth). Further investigation is needed to fully understand how temperature growth indicates general feelings and changes in feelings towards robots during an interaction.

Face distance also stood out as a measure linked to the questionnaire data. Lower technophobia, a non-engineering background, lower age, and finding the experiment "not scary" tended to have farther face distances. These results match previous findings on robot perception and personal space [17]. Face distance from the robot may be difficult to draw conclusions from, as several potential factors can affect face distance. For example, people afraid of the robot (such as fear of getting hurt or breaking the robot) or people disinterested in the experiment may take a farther distance from the robot. However, the results in this study show that people who are afraid of technology in fact get closer to the robot than those who are not. Getting too close to the robot can also indicate a lack of affordance of "personal space" to the robot, and thus a form of objectification of the robot. For example, one subject was so interested in the robot's machinery that the subject forcefully hit the robot to see how its autobalancing reacted. Subjects who rated the interaction as "meaningful" showed an opposite pattern from the other pro-robot questionnaire items, and had closer distances to the robot than those who found the study "meaningless". We conjecture that the measure of "meaningful" versus "meaningless" is also a measure of the subject's interest in the study, and perhaps subjects who found the experiment meaningless were less engaged and did not come close to the robot. Thus, we believe there are two factors affecting a subject's face distance to the robot in opposing directions: their objectification of the robot and their engagement in the task. While it is difficult to interpret face distance measurements only, when combined with temperature and temperature growth measurements, they may create a stronger picture of the user's feelings.

Tactile measurements also showed some patterns relating to the survey data. Higher technophobia was linked with lower tactile measurements, which likely reflects a resistance to interacting with the robot. On the other hand, subjects with an engineering background had higher tactile measurements – likely because they were used to interacting with similar machinery, and were closely inspecting the robot's architecture. Subjects who said they benefitted from the robot's touch also tended to have higher tactile measurements, indicating that these subjects were potentially more eager to touch the robot. While these tactile correlations seem to have meaningful links to the subjects' feelings about the robot, tactile measurements had some of the weakest correlations. No questionnaire items resulted in significant correlations in the same direction in all eight tactile sensors, and only one resulted in correlations in seven out of eight (the item on how touching the robot affected the subject). Overall, tactile pressure readings may be useful as additional measurements for a larger repertoire of sensor data, but do not act as strong evidence in interpreting a subject's feelings towards an interaction with a robot.

While there were many significant correlations, some measures and questions were less effective. Questionnaire items not reported in this study did not have strong sensor data correlations, such as one item asking the subject to circle personality adjectives that they would attribute to the robot. Sensor data likely represents only a subset of feelings a subject may feel towards a robot, and identifying which sensors match with which specific subsets will be an important next step. For example, while temperature data may indicate relaxation with the robot, it is unlikely to be directly linked to aesthetic evaluation of the robot. In terms of sensor measurements, force data on the arm had no clear tendencies for any questionnaire item. However, data taken by grasping the hand (tactile and temperature data) seemed to be enough to make connections with the questionnaire data. There is also the question that while all of the above correlations are very significant, many of their correlation coefficients are not very high. This means that while it may be difficult to predict a user's feelings just based on one of these measures, there is still a significant relationship between the survey data and the sensor data. There are enough significant correlations showing the same tendencies, matching those in previous studies [11] to avoid the possibility of "data dredging". Ultimately, these sensors can be very sensitive, and so a combination of several measurements is key to being able to interpret subjects' feelings towards a robot.

Overall, the sensor measurements of temperature, temperature growth, tactile force, and face distance seem to be possible candidates to be used as new, objective measures for HRI experiments. These measurements had been first proposed in our previous research [10,11], and the current study confirms their potential through using them in a structured, experimental setting. Engineers should reconsider the sensors on their robots not just as environment-sensing tools, but as valuable people-sensing tools. Most sensors are inexpensive, small, and easy to attach – allowing the experimenter to instantly be able to take gigabytes of data about any interaction with the robot. This study demonstrates the particular effectiveness of temperature sensors on the palm and fingers of a robot's hand as a natural sensor interface. For future research, skin conductance sensors could provide additional evidence of user stress, although current sensors are limited in terms of size and data consistency.

While these correlations show general tendencies – as individual differences are factored out by the large number of diverse subjects – the next step is to focus this research on the individual. If a robot could use a learning model to assess a user's feelings and stress in real-time based on user baseline information, then the robot could dynamically adapt to the user. These data measurements can also be used in place of or in conjunction with survey and behavioral data during an HRI experiment, to look at demographic differences in HRI or to compare reactions to different robot behaviors. It will also be important to investigate other sensor measurements that can still be natural and discreet but add to the picture of how a user feels towards a robot.

V. CONCLUSION

This study proposed and explored a methodology by which sensor data from a humanoid robot taken during an interaction could be used to measure users' reactions to the robot. Significant correlations between these sensor data, users' technophobia scores, and a post-experiment survey confirm that sensor data – particularly hand temperature, temperature growth, face distance, and tactile pressure – do act as biosignal measurements, and do reflect the user's psychological state. Specifically, it appears that higher hand temperature, higher temperature growth, higher tactile measurements, and farther face distances may correspond to more positive reactions to a robot. This methodology could potentially be used as an objective measure to support survey data taken during HRI experiments. In the future, experiments could use this methodology to look at demographic differences in HRI, and also to develop predictive models of a user's changing feelings towards a robot.

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