A thermal emotion classifier for improved human-robot interaction

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***Abstract*— In their expanding role as tutors, home and healthcare assistants, robots must effectively interact with individuals of varying ability and temperament. Indeed, deploying robots in long-term social engagements will almost certainly require robots to reliably detect and adapt to changes in the demeanor of social partners to promote trust and more productive collaboration. However, the recognition of emotional state typically relies on the interpretation of very subtle cues, often varying from one person to the next. In addition, while facial expressions, body posture and features of speech have been used to detect affective changes, the robustness of these measures is often hindered by cultural and age differences. Recently, infrared thermography has shown promise in detecting guilt, fear and stress, indicating that it may be a viable sensing modality for improved human-robot interaction. In this study, we evaluated the efficacy of using a far infrared (FIR) camera for detecting robot-elicited affective response compared to video-elicited affective response by tracking thermal changes in five areas of the face. Further, we analyzed localized changes in the face to assess whether thermal and electrodermal responses to emotions elicited by video and by robots are similar. Finally, we performed principal component analysis to reduce the dimensionality of the data set and evaluated the performance using machine learning techniques for classifying thermal data by emotion state, resulting in a thermal classifier with a performance accuracy of 77.5%.**

I. Introduction

Collecting physiological information remotely creates opportunities for promoting long-term, productive, and safer interactive work between humans and the systems with which they interact. However, while FIR sensing provides copious amounts of physiological information, it is a sensing modality that is still poorly characterized for human-robot interaction.

The recent profusion of robots working in close proximity to humans motivates the development of robots capable of detecting less overt signs of changing emotional state in their human counterparts. For robots employed in educational and therapeutic settings, thermal feedback indicating increased stress level and frustration would enable robots to adjust their interactions to challenge students and patients optimally without exceeding their ability.

Further, thermal sensing may offer assistance to developmentally disabled populations and other individuals who have a limited ability to communicate and those who may be averse to wearing biofeedback sensors. By detecting the innate emotional and stress state of the individual without the requirement of self-awareness or speech, thermal sensing may be a valuable tool for improving our understanding of the affective impact of robot interactions on populations with a limited ability to self-describe or express emotional state.

Thermographic sensing has mostly recently been used to identify distinct thermal patterns for performing face recognition, facial expression detection and the estimation of individual affect [1, 2]. Studies have even demonstrated that fear can be distinguishable from a happy affective state and that guilt manifests in a thermographically unique way from a neutral baseline state in children [7].

Infrared thermography offers many advantages over other modalities of emotion detection. First, because thermal cameras capture data outside the visible light spectrum, the information they deliver is less prone to changes in illumination, shadows and partial occlusions. Further, thermographic changes associated with physiological response do not rely on facial expression, body posture or features of speech so it remains impartial to variances in age, culture or language. Moreover, because thermography is collected remotely, it may be integrated into a wide range of human-robot interaction settings and applications. This work evaluates both the elicitation of emotion with a robot as well as a classifier for discriminating between two emotion states.

II. Related Work

A. Applications in robotics.

Thermal imaging has been employed in a number of applications to detect affective change in individuals exposed to emotional stimuli [14]. However, while studies exist which include contact-based sensors for affect detection in human-robot collaboration, there is a paucity of published work in which noncontact sensing is employed for this purpose. This study specifically explores the efficacy of eliciting emotion with a robot and delivers a trained 2-state thermal classifier for those emotions.

B. Classifying emotion states.

Research in infrared thermography has accelerated in the last decade, revealing the significant potential of this sensing modality for greatly improved sensing and enhanced robot adaptivity in human-robot interactions. For instance, anxiety caused by lying has been demonstrated to increase the surface temperature of the periorbital area of the face and the tip of the nose [1], while increased mental workload has been correlated with nose tip temperature decreases [8]. Fear in adults has been associated with rapid decreases in cheek temperature and an increased temperature in the periorbital region, while

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infants experiencing the stress caused by maternal separation, typically present a decreased overall forehead temperature [3, 4]. Children who feel guilt after breaking an experimenter's "favorite" toy, exhibit a significant temperature decrease in the tip of their nose [7]. These examples not only illustrate the significance of skin surface temperature for assessing the psychological states, but also serve to reveal the inherent value of using these fundamental physiological cues to inform and improve robots employed to assist individuals in their day-to-day lives.

C. *Other physiological measures of emotion.*

Physiological signs associated with emotional response include increases or decreases in heart rate, changes in skin tone from blushing or turning pale and perspiration [5]. Biofeedback sensing and RGB video-based techniques have been applied to detect changes in these autonomic nervous system responses and to track affective response. Research has also explored collecting data from wearable electrodermal sensors as part of a multimodal approach to detect emotional or psychological stress [4, 6, 10]. However, few studies explore the elicitation of anger with a robot and fewer describe a thermal classifier for use in human-robot interaction.

III. METHODOLOGY

In this study, we developed two interactive sessions with a robot and selected three sets of video clips to elicit affective response to anger and happiness. We collected physiological measures from each participant including thermal information from five regions of the face and electrodermal activity (EDA). Additionally, a Likert scale was administered after each robot session and after each set of video clips to record individual feedback pertaining to emotional response. We were interested in comparing differences in thermal affective response elicited with well-studied stimuli such as videos to those elicited via human-robot interaction. Further, we evaluated the performance of classifiers to further describe features contributing most significantly to each emotion.

Each study session was divided into four individual phases. The first two phases engaged participants with two versions of an interactive robot. In phase 1, participants engaged in a pleasant interaction with a complimentary robot while the second phase was designed to be frustrating and anger-inducing. The last three phases consisted of a set of clips acting as a "break" between the robot condition and video condition and two sets of video clips designed to elicit happiness and anger, respectively.

A. *Participants.*

Ten healthy adult participants participated in the study which included two interactive sessions with a robot and three video sessions, lasting a total of approximately 30 minutes. Participants were asked to sign a study consent form and video release form and to wear an EDA sensor on their wrist before beginning the study.

B. *Thermal camera.*

The InfrREC R300SR-S high resolution infrared video camera with a thermal sensitivity (NETD) of 0.025°C was employed to collected temperatures. The camera simultaneously captured RGB and thermal video at approximately 60 frames per second and streamed data in real-time to a computer attached via USB. All collected thermal data was processed and stored on an encrypted laptop.

C. *Robot condition.*

The robot used in this study was a modified version of MyKeepon with programmable servos controlled by an Arduino board [12]. MyKeepon has a minimalistic design that resembles a small, yellow snowman. Four degrees of freedom allow the robot to pan to the sides, tilt forward and backward, bop up and down and roll to the sides. Several nonverbal behaviors such as idling, happy, surprise and confusion were combined with Text-To-Speech (TTS) utterances using the Thalamus framework [11] to animate the robot. The interface implemented for this study was tele-operated to control MyKeepon's higher-level actions, such as greeting the user or asking the next trivia question.

D. *Video condition.*

Two video sets were selected to elicit happiness and anger based on criteria defined in [13]. The first set included two movie clips to elicit happiness and included scenes from "Elf" and "Emperor's New Groove". The second set of film clips elicited anger and included scenes from "Enough" and "12 Years a Slave". Each video clip lasted approximately 2.5 minutes, for a total of 5 minutes for each video set.

E. *EDA.*

The Empatica E3 electrodermal activity (EDA) sensor was used to collect EDA during each session. The sensor was placed on the dominant hand of each participant approximately 5 minutes before entering the experiment room and data was collected throughout the entire study session and monitored via Bluetooth connection on a nearby smartphone.

F. *Likert scale.*

Self-reports were collected with a 6-point Likert scale, representing the intensity of emotion experienced (0-5) for a range of 6 possible emotions including: happiness, surprise, sadness, frustration, anger and disgust. To avoid bias, the identical scale and range of emotions was included in every survey after each phase of each study session.

G. *Experiment room.*

The study was conducted in a small experiment room at the Yale Child Study Center. One chair and a small table were positioned in the middle of the experiment room. The robot was placed on the small table and a set of speakers, used to output the robot's sounds, were positioned behind a small wall in the room. Additionally, a computer monitor and a thermal camera mounted on a tripod, were placed opposite the table and chair. The room was divided by a heavy black curtain behind which two experimenters remained for the duration of each session to monitor the thermal camera and tele-operate the robot, as needed.

H. *Protocol*

Upon entering the experiment room, each participant was

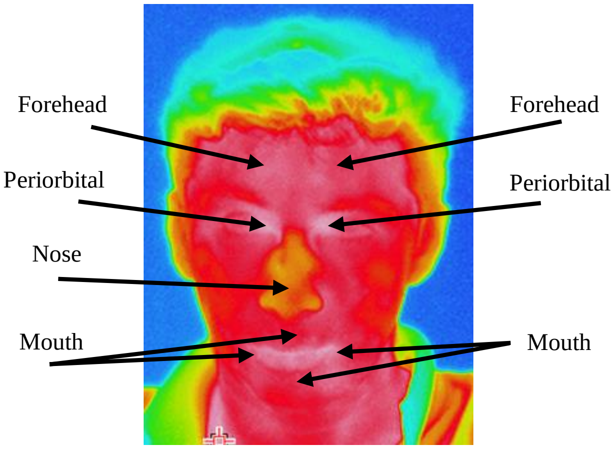

Figure 1. Facial regions of interest (ROIs)

asked to sit in a chair located in front of the small table. The study facilitator explained that the participant was invited to engage in a 30-40 minute session featuring two trivia games with the robot and three sets of video clips. It was explained that the robot would deliver a trivia question, present four possible answers (each denoted as answer "A" through "D") and the participant would be asked to speak their letter answer to the robot. The robot would then repeat the participant's answer and respond as to whether the given answer was correct or incorrect. Participants were informed that several features related to the robot's performance were being tested. Additionally, the study facilitator explained that a tablet-based questionnaire would be provided at the end of each phase to capture their personal evaluation about each phase.

PHASE I: Robot/Happy. In phase I the robot introduced itself and described the rules of the trivia game. Trivia questions in this first phase were designed to be relatively easy, with the correct answer being (mostly) evident to participants. With each correct response, the robot delivered positive feedback such as, "Great job!", "You are really smart!" or "You have the highest score!" If an incorrect response was given, the robot gave the participant the opportunity to keep trying new answers until the correct answer was received. A total of 10 trivia questions were presented in Phase I, for a total duration of approximately 5 minutes. Upon completion of Phase I, participants were asked to complete a Likert scale questionnaire to collect emotional feedback pertaining to this phase.

PHASE II: Robot/Angry. Phase II began with the robot delivering positive feedback about the participant's performance in the previous phase and a brief introduction for the Phase II set of trivia questions. In this phase, the robot delivered trivia questions of greater difficulty. In this phase, however, the robot intentionally selected an incorrect answer for seven out of the 10 questions presented and repeated that answer (as if the participant had actually selected it) before informing the participant that they had answered incorrectly. Phase II was approximately 5 minutes in length and consisted of a total of 10 trivia questions. At the end of this phase, participants were again asked to complete a Likert scale questionnaire describing their emotional evaluation of the Phase II interaction.

PHASES III-IV: Video/Happy, Video/Angry. Phases III-IV featured film clips that were selected to elicit happiness and anger, respectively. At the completion of each set of videos, participants were also asked to complete a Likert scale to report their evaluation of each video stimuli. Additionally, before the beginning of video sets 1 and 2 a neutral video, featuring slow moving geometric shapes and soothing music, was played for 30 seconds.

IV. Data Collection

A. *Thermal video.*

A thermal camera was positioned approximately 4-5 feet from the participant so that the field of view was centered and the participant's entire face was captured throughout all four of the study phases. During each study session, thermal and RGB video were simultaneously streamed in real time to a nearby computer. In the event that a participant changed their position so much that their face was no longer in the camera's field of view, the participant was either asked to readjust their position, or the camera position was adjusted.

B. *EDA.*

EDA was collected from each participant beginning several minutes before entering the experiment room and throughout the duration of the entire study session. EDA signals were deemed to be viable when the minimum skin conductance level (SCL) equaled or exceeded 0.4 microsiemens (µS) and displayed a variance of at least 0.2 µS throughout the course of the study session.

C. *Likert scale.*

The Likert scale was electronically administered via tablet, in order to provide the opportunity for each participant to easily self-report their emotional evaluation of each study phase.

V. Data Analysis

Data from thermal video, EDA, heart rate and Likert scales were collected along with the time-stamps for stimuli delivered during both robot and video conditions. We evaluated Likert self-reports from both conditions to evaluate the efficacy of emotion-elicitation via robot interaction compared to emotion-elicitation using a set of video clips. Further, we examined the thermal trends of five regions of interest (ROIs) (Figure 1) and EDA within each study phase to examine association to detect each emotion, in each condition. Finally, we reduced the dimensionality of the data set and trained and tested a thermal classifier with the most significant principal components representative of the data set collected. In order to conduct comprehensive analyses, data sets were each sampled, cleaned and time-synchronized.

We were interested in directly comparing robot-elicited and video-elicited thermal responses. Because we did not develop a sadness-eliciting interaction with the robot, we did not include analyses of video responses to sad stimuli here.

A. *Preparing the data.*

First, all ROIs including the forehead, periorbital region, tip

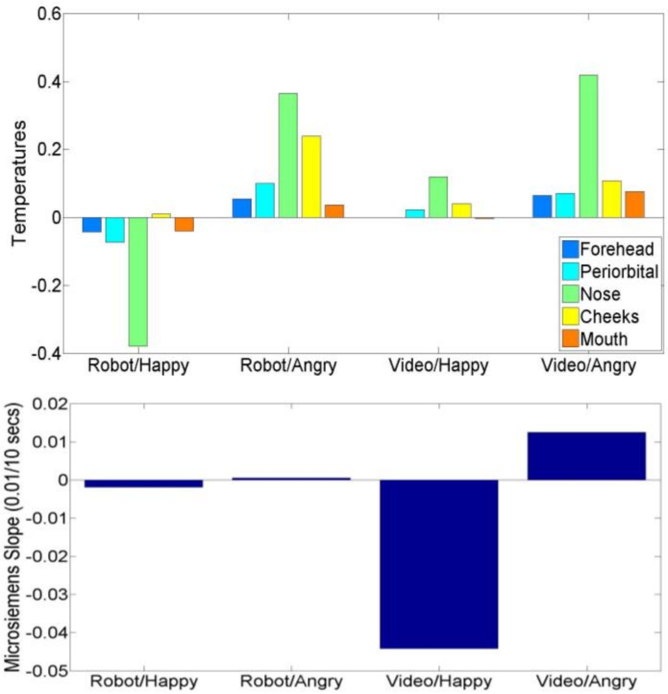

Figure 2. Thermal slopes (top) and EDA slopes (bottom) for each of the four study conditions. Columns of thermal features (top) forehead, periorbital area, nose, cheeks and mouth.

of the nose, cheeks and mouth, were hand annotated from the thermal video at 10-second intervals for the entire session duration and for each participant. Ten frames of thermal data were extracted at each ten-second interval for subsequent analysis. Next, we time-aligned extracted thermal readings, EDA, heart rate and Likert reports using recorded system time stamps in order to perform analyses across all data sets. Finally, due to variability in resting skin surface temperatures between participants and to more precisely measure physiological affect directly resulting from each stimulus, the within-phase mean and slope were computed for recorded ROI temperatures and EDA during each of the four study phases.

B. Objectives.

Two data sets (thermal and EDA) from two conditions (robot and video) were analyzed using Pearson's bivariate correlations, ANOVA linear models, principal component analysis (PCA), logistic regression and a support vector machine (SVM) to further our understanding of four primary research aims:

1. Assess the extent to which it is possible to elicit happiness and anger with robot interactions as it is with video stimuli
2. Evaluate if anger and happiness, when elicited by both video and robot interactions, result in thermally similar changes.
3. Explore the relationship between thermal data and EDA.
4. Perform principal component analysis to reduce dimensionality of data. Conduct logistic regression and train a classifier, effectively distinguishing facial thermal changes corresponding to happy and angry emotion states.

1. Eliciting anger and happiness using video stimuli and human-robot interactions.

Scores from self-reports collected after each study phase were assessed to evaluate the congruence between reported and elicited emotions. If a participant reported anger as the highest score compared to other emotions during an angry phase, even if another emotion was tied for the highest score, that elicitation was considered effective. Otherwise, the emotion elicitation was not considered successful. Correlations between emotion reports and each corresponding study phase were computed and the percentage of self-reports consistent with the emotion being elicited were derived.

2. Eliciting anger and happiness, via video and robot interactions, to assess thermally similarity.

Physiological time-series are often non-stationary in the sense that the system state changes in time such that taking averages will tend to destroy features that we are interested in preserving [9]. Since we were particularly interested in preserving and analyzing within-slope thermal changes resulting from within-phase stimuli, slopes were calculated for each ROI and for each participant to characterize thermal trends occurring during each condition.

3. Connection between thermal data and EDA.

We also evaluated the connection between collected thermal response and EDA within the robot condition, the video condition and the combined set. EDA slope was computed to examine changes occurring during happy and angry phases, to compare to within-phase changes observed in the thermal data, and to evaluate disparities between conditions for similar emotion states. Finally, we performed a correlation analysis of thermal and EDA features to further explore the relatedness between the two physiological measures.

4. Principal component analysis, logistic regression, classifier training.

Principal component analysis (PCA) was performed to reduce the variable set and to identify the most significant components contributing to the variability of collected thermal. PCA was first conducted with thermal data and separately, with EDA data to derive individual components for each dataset. Next, Pearson's bivariate correlations were computed to evaluate the correlation between thermal and EDA features and binary logistic regression was performed to model the conditional probabilities of collected thermal data predictive of two emotion states.

Finally, a support vector machine (SVM) was trained using leave-one-out training, where "one" corresponds to an entire participant set (two robot conditions and two video conditions). Selecting the appropriate kernel type, along with feature selection, is known to significantly impact classification accuracy in emotional classification of physiological signals and there is evidence that a linear kernel may achieve the best performance for classifying emotion from nonstationary signals [8]. Our analyses included an examination of linear, radial and polynomial kernels to achieve optimal performance with the thermal data collected.

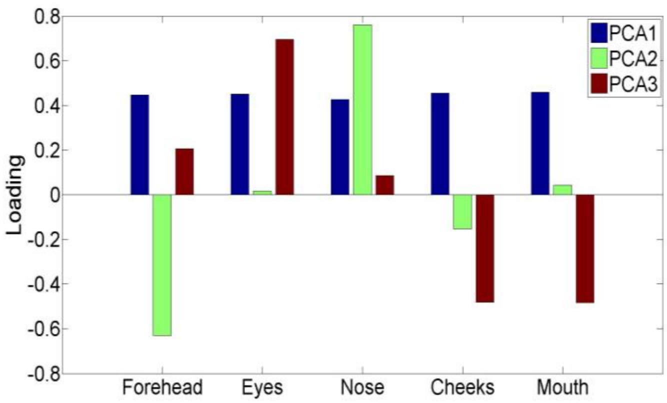

Figure 3. First three components for each feature, PCA.

VI. RESULTS

A. Eliciting anger and happiness using video stimuli and human-robot interactions.

As expected, self-reported happy and angry emotions were shown to be highly associated with the corresponding emotion phase *(r=0.860)*. Accordingly, approximately 93.0% of participants' responses indicated that the intended emotion was most significantly elicited emotion during the corresponding study phase.

B. Evaluate if anger and happiness, when elicited by video and robot interactions, result in thermally similar changes

Analysis of thermal data yielded several findings. Facial temperatures collected from participants during the robot condition and the video condition resulted in similar trends for corresponding emotion phases. In both happy phases, declining or flattening of slopes was observed while increasing slopes characterized angry phases (Figure 2). Thermal responses recorded for each of the five ROIs were quite similar between conditions as well, with nose temperatures accounting for the greatest thermal shift between angry and happy phases. Other ROIs revealed changes of similar magnitude and direction during the elicitation of angry and happy emotions.

These observations are further supported by univariate two-way ANOVA analyses with a Tukey control for multiple comparisons, in which we examined the interaction effects of condition (robot/video) and emotion (happy/angry) on individual facial ROIs. Results indicated that although there were no interaction effects for most of the ROI slopes, there was a strong, statistically significant effect between within-phase nose temperature changes, condition and emotion ($F(3,36)=3.523$, $p=0.025$).

C. Connection between IR and EDA.

Declining nose tip temperatures seemed to be related to declining EDA during happy phases as well. Consistent with the connection between lowered nose temperatures in both happy robot and happy video conditions, 75% of the dataset also revealed a decrease in EDA during happy phases, irrespective of condition. However, mean EDA slopes recorded during both robot phases were considerably less pronounced than those collected during the video phases (Figure 2) and no significant correlation resulted between thermal changes in emotion phases and EDA.

While contrary to our expectations, the lack of connection between EDA and thermal slopes may suggest an underlying difference between physiological responses recorded with EDA sensing and our thermographic camera. For example, a relatively delayed onset and slower recovery from thermal events may have contributed to within-phase differences between data sets. However, given that self-reports collected from the Likert scales are consistent with the emotion phase, thermal slopes increase and recover as expected across emotion phases and there is no significant correlation of EDA to emotion phases in this study, further investigation of EDA using additional signal processing techniques may be required to uncover the possible connection.

D. *Principal component analysis, logistic regression, classifier training.*

Principal component analysis (PCA). Five thermal features, including slopes for each of the five ROIs, were used to compute PCA (Figure 3). Results show that more than 90% of the variance was explained by the first three components, with 80.7% of that variance explained by the first two components. A summary of PCA findings is included below.

Component Loading. A Pearson's bivariate analysis was performed to further describe the connection between individual ROIs and each principal component (Table 1). All five ROIs loaded positively onto principal component 1 (PC1). Conversely, only two features loaded significantly onto principal component 2 (PC2), with the forehead negatively correlated and the nose positively correlated. Finally, three distinct ROIs loaded onto component 3 (PC3), including the periorbital region, cheeks and mouth.

Logistic regression and Support Vector Machine (SVM). Next, a logistic regression was computed to explore the collective value of thermal data, as informed by PCA, for predicting membership in emotion phases. To more specifically examine the interaction effects of condition and emotion state, individual dependent variables were tested. Results from logistic regression analyses are described.

Thermal slopes from the robot-only phases clearly distinguished between happy and angry phases (chi square = 27.726, $p < 0.001$ with df = 5) and a prediction success of 100%. Thermal data was not as predictive of emotion state when solely evaluating the video condition (chi square = 2.353, p=0.798 with df = 5), resulting in a prediction success of slightly above chance at 60%. When the two ROI slopes most significantly correlated with PCA1 and PCA2 in both conditions were applied, emotions were more reliably predicted (chi square 7.302, p=0.029 with df=2) with a performance accuracy of 77.5%.

Finally, we employed results observed from logistic regression and PCA to train an SVM selecting the ROIs found to most significantly discriminate between condition and emotion phase. Subsets of thermal data loading across PCA1, PCA2 and PCA3 were evaluated using leave-one-out training with the best performance resulting from forehead, nose and

Table 1. ROI loading on principal components. **denotes p<0.01

ROI/Component	PC1	PC2	PC3
Forehead	**0.832****	**-0.474****	0.147
Periorbital	**0.837****	0.013	**0.496****
Nose	**0.792****	**0.574****	0.059
Cheeks	**0.847****	-0.117	**-0.342***
Mouth	**0.854****	0.032	**-0.346***

cheeks slopes training, and an accuracy of 77.5%.

E. Study limitations.

The expectation that video-elicited thermal responses would be more pronounced than robot-elicited responses (and would take longer to recover thermally) led to the current study design in which robot condition was always presented first and the video condition, second. However, it is possible that emotion responses and corresponding thermal responses resulted in a cumulative interaction effect. A follow up study will counterbalance stimuli across condition and emotion.

VII. CONCLUSIONS

In this study, we developed two emotion-eliciting robot interactions and two sets of emotion-eliciting videos to explore thermal features contributing to the prediction of emotion state and to ultimately train a classifier for use in human-robot applications. First, we evaluated the efficacy of eliciting happiness and anger with robot interactions and video sets developed for this study using Likert-based self-reports. Ratings extracted from self-reports indicated that the participants' subjective appraisal of emotional stimuli for the corresponding emotion phase were consistent.

We further examined temperature changes in each facial ROI to compare thermal patterns occurring during human-robot interactions with those occurring during the observation of video clips. Univariate analyses revealed a strong, interaction effect between within-phase nose slopes, robot/video condition and emotion. Next, we explored the relationship between electrodermal activity (EDA) and thermal affective changes during the elicitation of anger and happiness in two robot and two video conditions. Although a significant connection did not result from analyses performed with EDA and thermal data in this study, future work may explore the use of additional signal processing techniques to yield additional insights describing their connection. Finally, we used PCA to identify which thermal ROIs were most predictive of condition and emotion state and guided the training of an SVM classifier using those features. Ultimately, an SVM 2-state emotion classifier, with a performance of 77.5% was achieved.

With an increasing research interest in exploring infrared thermography as a potential sensing modality for human-robot applications, investigating robust approaches for detecting changes in emotion state - especially during the course of human-robot interactions - is essential. This study delivers a comprehensive examination of the elicitation of two emotions during interactions with a robot and a methodological analysis describing thermal features contributing most significantly to each emotion.

Future work will more carefully explore the underlying cause for differences between thermal and EDA data collected during robot-induced and video-elicited emotional response to identify possible interaction effects. Additionally, a modified study protocol will be developed to counterbalance condition and emotion to mitigate the potential confound of cumulative thermal responses over time.

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