HADREB: Human Appraisals and (English) Descriptions of Robot Emotional Behaviors

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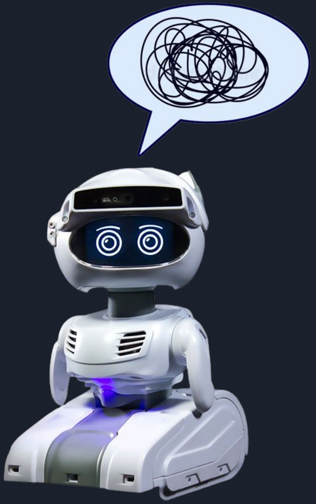
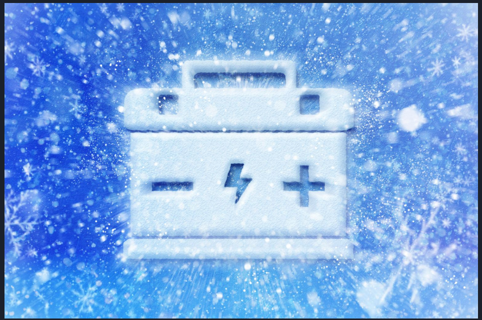
Introduction



- HADREB (Human Appraisals and Descriptions of Robot Emotional Behaviors) is a dataset of humans appraisals and descriptions of over 1,000 robot emotional behaviors.
- Dataset was collected from in-person participants using two robots as co-located communication is the setting for language learning in humans (Fillmore, 1981; McCune, 2008).
- We separate emotion labels into 8 positive and negative valence pairs of the 16 emotions from McNeill and Kennington (2019), and participants assigned a graded Likert-style label for each pair.
- Taking inspiration from Moseley et al. (2012) this dataset leverages the fact that humans anthropomorphize robot behaviors for emotional content by collecting human appraisals of observed robot behaviors, and we collect the corresponding behaviors—the robotic motor system—and descriptions to bring together the modalities of emotion, behaviors, and language.

Motivation



- Novikova et al. (2015) showed that humans anthropomorphize robots by attributing emotional content to robot behaviors.
- HADREB brings together descriptions and robot actions, allowing researchers to generate novel robot behavior using descriptions and to tie emotions and language to robot behaviors.
- Especially useful in solving the cold-start problem of spoken dialogue systems that have no prior knowledge of language (McNeill and Kennington, 2020) as emotions exists in humans before they learn language
- Emotion is also tied to the meanings of many words (Lane and Nadel, 2002); in particular, abstract words (e.g., democracy and utopia) are grounded in emotion (Vigliocco et al., 2013).

Related Work

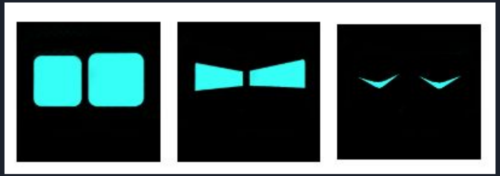
- Expands on the work done in McNeill and Kennington (2019), and allows our model to be used in incorporating emotion to language models possibly improving them and/or interactions between robots and humans.
- Comparable data collection efforts are relatively rare
  - Pena and Tanaka (2020) analyzed human perceptions of social robot's emotional states via facial and thermal expression but no dataset offered
  - Datasets for emotion in virtual agents have been gathered much relating to how persons perceive generated facial expressions (Beer et al., 2015; Randhavane et al., 2019; Beer et al., 2009).
  - Jam et al. (2021) proposes a data-driven method for increasing the number of emotion classes present in human-robot interactions.
- Existing models can infer emotions from text; our dataset puts emotion in physical context of where it is experienced and ties that to language

Misty and Cozmo

- two arms with 119 degrees of freedom
- two high-fidelity speakers
- moveable neck (pitch, yaw, and roll)
- 4” LCD image display/screen

- a lift for small objects
- track driving tread system
- a small OLED display screen for the face
- speaker for speech synthesis

Generating Behaviors



- Actions
  - Cozmo: head and lift position and left and right wheel speed/direction (duration parameter)
  - Misty: arm and head position (velocity parameter)
  - Range of values
- Faces
  - Cozmo: 13 face images recreated from existing examples
  - Misty: 11 face images preprogrammed
- Sounds
  - Cozmo: 14 utterance options (e.g. hhhh?, aa?, uu?)
  - Misty: 6 utterance options (e.g. oh!, hmm, oi)
- All behaviors 50% chance of action being generated with a randomized behavior length by randomly repeating the process 1-5 times resulting in 4-10 second behaviors

Participant Procedure

positive valence	negative valence
interest	alarm
understanding	confusion
relief	frustration
joy	sorrow
gratitude	anger
hope	fear
surprise	boredom
desire	disgust

1. invoke random behavior

2. describe and label each behavior for emotional content

3. log functions, responses

SDK Functions: display_face('2.jpg'), say_text('umm'), move_head(0, -5, 0, 80) drive_track(-28, 24, 1), move_lift(80, 80), ...

Description: narrowed eyes then looked down
Emotion Ratings: interest/alarm:3, confusion/understanding:3, frustration/relief:2, sorrow/joy:1, anger/gratitude:3, fear/hope:3, boredom:surprise:3, disgust:desire:3

Data

- Descriptions and respective emotion labels contained within dataframes in pkl files
  - https://github.com/bsu-slim/hadreb/tree/main/raw_data
- Functions
  - Cozmo: https://github.com/bsu-slim/hadreb/tree/main/cozmo_filtered/functions
  - Misty: https://github.com/bsu-slim/hadreb/tree/main/misty_filtered/functions
- Internal state data
  - Cozmo: https://github.com/bsu-slim/hadreb/tree/main/cozmo_filtered/states
    - lift angle and height, head angle, left and right wheel speed, if picked up, cliff detected, has in progress actions... (43 variables)
  - Misty: https://github.com/bsu-slim/hadreb/tree/main/misty_filtered/states
    - head pitch, roll and yaw angles and velocity, left arm and right arm angles, x, y, and z acceleration values (11 variables)

Recreating the robot behaviors

- Cozmo
  - https://github.com/bsu-slim/hadreb/blob/main/src/extract_cozmo_states.py
- Misty
  - https://github.com/bsu-slim/hadreb/blob/main/src/extract_misty_states.py

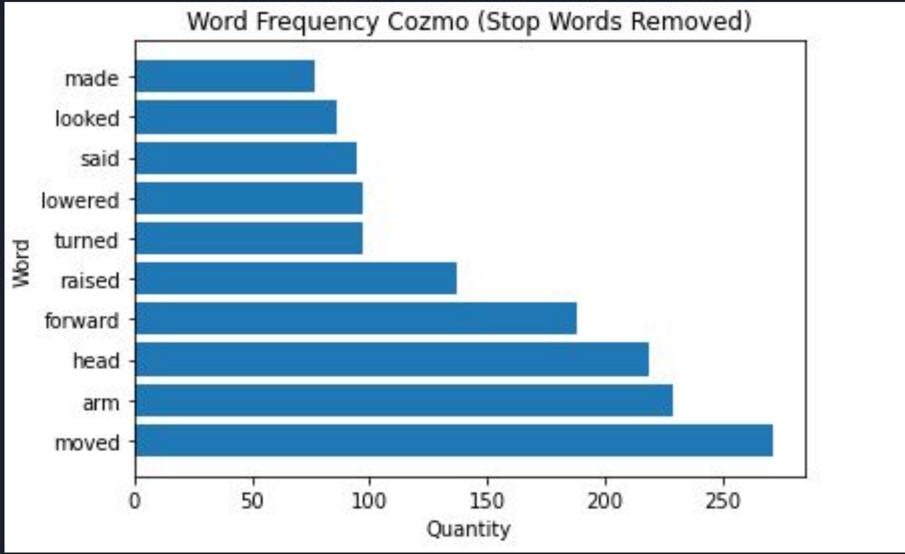
Data Processing

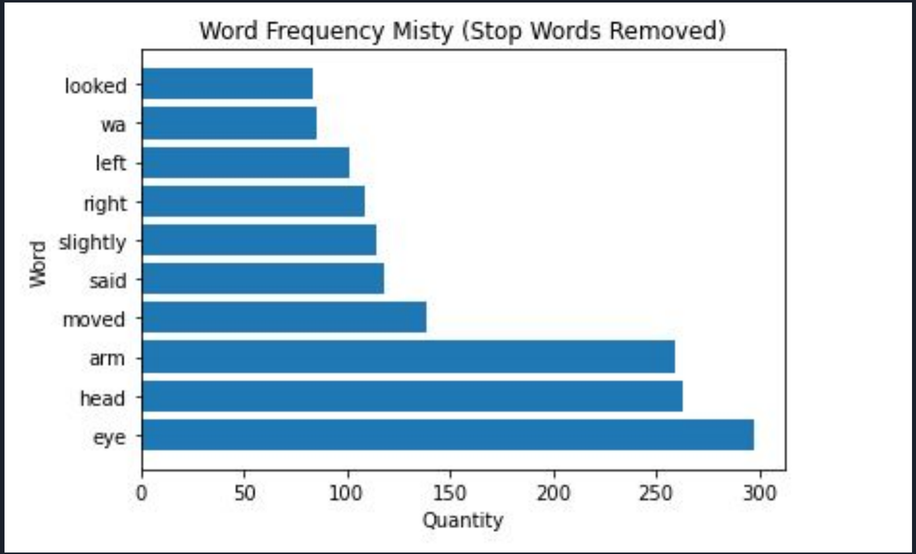
- Duplicate IDs
  - Removed any duplicate data entries (Comzo: 10; Misty: 27)
- No behavior
  - Removed behaviors where robot was described to have “did nothing” or “glitched out”. Found entries where all 3’s were given and manually looked through descriptions for descriptions of no behavior (Cozmo: 12; Misty: 1)
- Empty entries
  - Removed data with empty entries (Comzo: 1)
- Lack of internal state data
  - Entries where description and emotion label did not have corresponding internal state data or vice versa (Cozmo: 82; Misty 99)
- Total
  - Cozmo: 547
  - Misty: 545

Data Analysis: Emotion Labels

Emotion Pair	Cozmo Mean (STD)	Misty Mean (STD)
Interest/Alarm	2.39 (1.04)	2.7 (1.24)
Confusion/Underst.	2.78 (0.99)	2.86 (1.74)
Frustration/Relief	2.92 (0.77)	2.92 (0.82)
Sorrow/Joy	2.9 (0.86)	2.96 (0.91)
Anger/Gratitude	2.96 (0.7)	2.96 (0.83)
Fear/Hope	3.07 (0.75)	2.99 (0.81)
Boredom/Surprise	3.08 (0.82)	3.18 (1.09)
Disgust/Desire	3.13 (0.84)	3.05 (0.86)

Data Analysis: Descriptions





Analysis: Internal State Data

- https://github.com/bsu-slim/hadreb/blob/main/analyses/RobotBehaivorDataAnalysis.ipynb

Experiments

Setting	f1 score	accuracy
Cozmo train/eval	58.29	79.61
Misty train/eval	53.51	74.86
Cozmo train, Misty eval	54.36	76.35
Misty train, Cozmo eval	51.27	69.12
Moro et al. (2020)	57.0	91.0

- Experiment 1: Descriptions to Emotions
  - https://github.com/bsu-slim/hadreb/blob/main/src/zero-shot.ipynb
  - For each description, used a BART pipeline to produce a distribution over the 16 emotion labels. Took the label with the highest probability and compared it to true emotion labels. Full point for 1 or 5 and half point for 2 or 4. Cases with 3 were ignored (as it's neutral)
  - Misty: 79.3%; Cozmo: 69.5%
- Experiment 2: Robotic States to Emotions
  - https://github.com/bsu-slim/hadreb/blob/main/src/semdial2020_model.ipynb
  - Mapped internal states to set of features derived from Novikova et al. (2015) termed Novikova features
  - 9 novikova features were used (e.g. Transfer weight forward (head bent or movement forward) and Approach 3 - Move its body forward (track wheel movement forward) (percentage of state updates where true)
  - Used multinomial K-Nearest Neighbor classifier (Zhang and Zhou, 2007) same as done in Moro et al. (2020). K is 5.

Conclusion

- HADREB dataset provides a rich resource for human perception of robots' emotional states in human-robot interaction. especially given the in-person, co-located environment
- Analysis of dataset provides insights on how the abilities of two robots and their differences affect the perceived 'emotional' states of these robots for human observers
- Dataset proven to be useful using zero-shot learning task and k-nearest neighbor classifier to map from descriptions to labels and internal states to labels respectively
- Dataset and analysis limited due to small size of data which may cause lack of results that are present in larger datasets of the same kind
- Plan on future releases of the dataset with more data


Thank You!

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