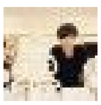
Reading 3

Review of Maintaining awareness of the focus of attention of a conversation: A robot-centric reinforcement learning approach

Subscribed

- Review of Spatial and other social engagement cues in a child-robot interaction: Effects of a sidekick

Display mode Display replies flat, with oldest first Display replies flat, with newest first Display replies in threaded form Display replies in nested form



Review of Maintaining awareness of the focus of attention of a conversation: A robot-centric reinforcement learning approach

by Bo Cao - Monday, February 6, 2017, 6:51 AM

1. Briefly state what contribution the paper makes to the field of Human-Robot Interaction in your view. Use this field to summarize the contribution (not the flaws) of this work.

This paper proposed a new approach of reinforcement learning to finding Good policies for robot to convey attentiveness. These policies are able to generalize among interactions with various number of people. In addition, they can handle various levels of sensing noise.

In addition, they also developed a robot-centered state representation for reinforcement learning, which is agnostic to the number of people who is interacting with the robot.

1. Write your full review of the paper here, including strengths and weaknesses. Think about:

Strengths:

This paper proposed a novel idea of robots conveying attentiveness by using reinforcement learning to searching good policies.

Clearly citation of prior work from social physiology, implementation, experiment and evaluation.

Figures, simulation model steps, parameters, experiments procedures are clear.

Results are convincing.

Future work and limitation are well written.

Weaknesses:

People's position mentioned in the paper is static, could it work in a dynamic people group environment? There were experiments mentioned in VI RESULTS, C. Individual Behaviors, when people slightly adjusted their positions. But in real world, there are some cases that a group of people are moving with respect to other people in the group like in a party.

There could be some cases where people are standing in a circle of o-space, but some might happen to be on the circle who are actually speaking loudly in the other o-space which is adjunct to this o-space. These outliers might speak more loudly than those who are actually in the real conversation in the o-space. According to the result of this paper, the robot could face towards to those outliers.

These policies worked in conversation in o-space, it would be great to test whether it could generalize in a non-o-space as well.

A robot cannot speak its opinion in the conversation is limited since in reality, when a group of people are talking on a topic, each one could be inspired by other people's opinion so that he/she would be desired to speak. So does a robot.

- Significance of the work's contribution to HRI and the benefit that others can gain from the contribution: why do the contribution and benefit matter?

A novel idea of generalizable state representation from robot-centric perspective using reinforcement learning.

Robots using this approach can find policies to convey attentiveness with some level of noise tolerance.

Because this paper proposed an approach to address the problem of how a robot should pay its attention in a group of human's conversation. Further study can be conducted based on the result of this paper. These studies can be but not limited to 1) a robot can not only express its attentiveness to the speaker, but also find the right time to speak its opinion; 2) multimodal expressing attentiveness including gaze (like eye ball orientation).

Some types of social robots can benefit from this work, including companion robot and educational robot.

- Originality of the work: what new ideas or approaches are introduced?

Reinforcement learning for robot to learn policies to convey attentiveness.

These policies are generalizable across various numbers of people.

Using o-space for human-robot interaction.

Discount rate was introduced when maximizing the total reward for next action.

- Validity of the work presented: how confidently can researchers and practitioners use the results?

According to figure 4, DYNA-2 and TEXPLORE have lower proportion(less than 0.1) of speakers towards whom the agents failed to orient as a function of the look-at noise. Using the results of both agents would be more reliable than the other two of Disc. Sarsa and Cont. Sarsa.

The this confidence is limited to the conditions mentioned in the paper:

- A robot with camera and a microphone array.
-
- People in the conversation are in o-space.
-
- The number of people range from 2 to 6.

Experiments with more number of people should be conducted to validate its higher generalization.

    - Presentation clarity;

The general approach, to be more specific, the action-value function was clear. The simulation was clear enough that other people could execute it directly.

Algorithm of learning and searching was clear.

Fig 2 (a) was described clearly in the description of this figure, as well as in III C Stride, other figures from Fig 2 (b) to (e) were described in III A Background.

6 Features are described clearly. But I don't see how these 6 features are designed, especially f2, f4 and f6, which are binary feature indicating whether their corresponding features were valid or not. The reason for using f2, f4, f6 was not so clear.

Figures of experiments were clear to show the results.

This paper mentioned that the robot had a camera and a microphone array, although the field of view was set to 80 degrees and 100 degrees respectively, no specific physical configuration about the camera and the microphone array, like how long or how much angle did the microphone array covered, were mentioned.

I was a little bit confused about Fig 9. The y-axis was described as "Prop. of steps with bonus". In the end of the description, it said "Error bars represent std. Errors.", so how did the error depicted in this figure?

    - Relevant previous work: is prior work adequately reviewed?

Papers related to expressing attention were reviewed, but limited to body orientation since this is what this paper focused on. However, I think prior works about the limitation of using body orientation to show attentiveness from purely the perspective of psychology and other cues from other modal like gaze should be included.

Other perspectives of the paper were adequately reviewed and each part cited prior works in its corresponding place. For example, the survey of reinforcement learning in robotics was reviewed. In f5, in page 4, the center proposal was inspired by prior work.

    - If you have concerns about the methodological or statistical approaches taken by the authors, or its level of advancement over prior work, please cite a source for your objection (e.g., a definitive paper, a set of professional guidelines or a standard textbook

Turning the body towards the speaker is a major way to showing attentiveness, but in reality there are also other ways to show that the robot is listening like gaze, or even just using “thinking gestures” to show that the robot is thinking of what speaker’s saying. [1][2] showed that “*interviewers are evaluated more attentive when their gaze is relatively high*”. There could be some cases when people is paying attention to the speaker using gaze cues, but not necessarily using the body orientation.

[1] Kleinke, C. L. (1986). Gaze and Eye Contact: A Research Review. Psychological Bulletin, 100(1):78–100.

[2] Nikolaus Bee. (2013). Affective and Attentive Interaction with Virtual Humans in Gaze-based Settings. Dissertation Universität Augsburg

Permalink | Reply

Re: Review of Maintaining awareness of the focus of attention of a conversation: A robot-centric reinforcement learning approach

by Bo Cao - Tuesday, February 7, 2017, 5:32 PM

Proof of attending Marynel Vazquez's talk.