Ad-Hoc Networks Project Report

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***Abstract*—This paper studies whether emotional expressions provided by a human observer can improve the learning performance of a reinforcement learning agent by influencing the exploration/exploitation trade-off in Q learning. When the human observer shows positive affect the agent tends more towards exploitation while negative affect will make the agent explore more.**

I. Introduction

A. Motivation and related work

II. Research question

A. Hypotheses

III. Method

A. Materials

1) Exploration/Exploitation Strategies:

2) EARL: Emotion, Adaptation and Reinforcement Learning Framework:

1) Emotion recognition module perceives human facial expressions in real time. For this we will be using Affectiva [**?**] (more in section **??**)
2) A reinforcement learning agent fed the recognized emotion as input.
3) An artificial emotion module slot can utilize all available information to produce artificial emotion of agent which can be later used as intrinsic reward or as input for the expression module.
4) An expression module aims to express robot emotion. This module consist of a robot head with different degrees of freedom(such as eyes, ears, lips and eyelids) to generate expressions.

B. Affectiva

C. Experimental setup / approach

1) Continuous environment:

2) Social learning and non-social learning:

D. Measures

E. Work plan

- Week 1.5: Finalize how the expressions will influence the temperature parameter.
- Week 1.6: Look further into the implementation details of the work of Broekens [**?**]
- Week 1.7: Adapt implementation and prepare experiment
- Week 1.8: Perform experiment with human observers
- Week 1.9: Finalize results, conlusion and discussion and prepare presentation
- Week 1.10: Give presentation

IV. Results

A. Discussion

V. Conclusion and further research

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