Academic English Assignment 1
Literature Review

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Quite some different approaches have been researched already on the topic of opponent position prediction, both in video games and other domains. In this section a few of them will be outlined to show the current state of research around the topic and how this research paper relates to these earlier works.
In the works of [2], two different models for opponent position prediction, Hidden Semi Markov Models and Particle Filters, are compared on how accurate as well as human like their predictions are. The comparison with human like prediction was carried out by comparing the performance to human prediction in a game setting of Capture the Flag. The research concludes on Hidden Semi Markov Models being the most accurate and making the most human like errors. It is clear that this research focuses mostly on the measurement of human-like prediction, but does not integrate such a prediction system in a game participating AI system.
[5] uses a Particle Filter as well, but unlike researching the likeness to human prediction, tries to find out if adding such a filter for position prediction in an AI system can enhance its performance. The EISBot for the game Star Craft was equipped with a Particle Filter and reasoning capabilities about different game states that actively use the prediction made by the filter. Results showed the new AI had a 10 percent increase in win percentage, but that making more game states available for the bot to reason about does not always improve the performance. Although the method of research has some resemblance to this paper, both evaluate the increase in performance of an existing bot, it takes place in a completely different game domain, Real Time Strategy instead of First Person Team games, and uses a different approach towards constructing a prediction model.
Instead of trying to predict the opponent's position, the authors of [3] focuses on creating a reasoner that anticipates behavior of an opponent in Quake. This was done by enhancing the Soar Quakebot with anticipation strategies, which are used only in case the bot has a high chance of successfully predicting what the opponent is about to do. If such an anticipating strategy is triggered, the Soar bot predicts the behaviour of the opponent by reasoning what he himself would do if in its opponent position. Although it is stated that these additions of anticipating strategies are beneficial for the performance of the AI, no results are mentioned that confirm this. The implementation of these anticipation strategies might not be solely for position prediction, but it does make some interesting points regarding the use of ones own behaviours to project what an opponent is going to do, something which could arguably adds a human-like dimension to the bot.
Not only video games deal with unobservable states, it is also a well known problem in robotics. In [1] is dealt with the same problem of position prediction with a goal of keeping service robots from getting in the way of humans in real life situations. To do so, these robots need to predict where humans are heading and what their intentions are. All aspects of these kinds of predictions are treated in this paper, for instance, using sensor data to sense humans and how to keep track of a single person. Both these aspects are less important for the game domain, as this information is generally known, but there are sections

that explain how Hidden Markov Models can successfully be used for learning motions patterns.
In [4] both the combination of making predictive models for opponent positions is discussed as well as a way of actively using these models to intercept opponents in a game. The predictive models were made using a particle filter that integrates both Maximum Entropy Inverse Reinforcement Learning motion models, as discussed in [6], and Brownian Motion models, from which the latter serves as a baseline performance test (by randomly spreading particles around the map). Maximum Entropy Inverse Reinforcement Learning gives the most accurate results to where the opponent may be. The work that will be presented in this research paper is closely related to the predictive models created by [4], and builds further upon Maximum Entropy Inverse Reinforcement Learning Motion Models by adding general behaviour classification and testing it in a different game environment, namely Capture the Flag.

References

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