Does Exploration Behaviour That is Based of (Human-Like) Curiosity Perceive AI Smartness?

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***Abstract*—The abstract goes here.**

I. Introduction

ARTIFICIAL intelligence (AI) in video games is very crucial when it's used as one of the main mechanics. Intelligent non-player characters (NPCs) are extremely hard to make due to the nature of it's complexity. The more complex it is the more outcomes developers will have to consider and the more problems will occur during development.

Explain curiosity - human behaviour often depends on person's intentions to explore. Why apply to AI? The aim of this paper is not to create curiosity-driven AI in Unreal Engine 4 (UE4), but to implement and test a particular behaviour and see how people react. Whether they like it or not, whether they think it behaves smart and etc. The aim of this implementation is to find a small nuance that can make the AI feel and act smarter.

Throughout the last 30 years researchers are trying to create intelligent AI using different methods and algorithms. Recent achievements in such are are really worthy of respect, for example, AlphaGo being able to beat world champions in Go (citation) or OpenAI playing Atari games and, in most of them, getting higher scores than player(citation required). AI in games, however, is used to create non-player characters (NPCs), which can be enemies, merchants, companions and a lot more. Some of the very complex algorithms, such as reinforcement learning (RL), deep Q-learning, curiosity-driven, evolution-based (add more or change) are being used in old games such as Atari as a test. However, due to specificity of games, it is not always the best solution. Depending on game's design, very simple methods can be used instead, or less complex than previously mentioned ones. As an example, Monte Carlo Tree Search (MCTS) became a common one to use after the success of the game F.E.A.R (i guess?) or Finite State Machine (FSM), which is also a very common one these days and is being used in most known games (citation required). Another widely spread technique is behaviour tree, which I'm going to use for this paper.

II. Related Work

The main focus of this paper is to (demonstrate) talk about a potentially valuable AI behaviour that is not complex yet efficient in demonstrating (implementing) smart AI. In Section III different AI implementation methods will be discussed, both complex and simple. Section IV will present (introduce) human's curiosity and discuss its importance towards one's willingness to discover and possibly relevant behaviour implementations to make smart AI. The testing material will be discussed in Section V, which will also include an explanation and use of Turing's test. Methodology and hypotheses will be reviewed in sections VI and VII respectively. The behaviour implementation will be made in Unreal Engine 4 (UE4) using our team's game for easier testing purpose as there will be enough assets to create a unique world which AI could be placed on.

- Explain the main focus of this paper
- Explain the testing subject I'm gonna use
- Briefly explain next sections
- Will be using my third year team project game to test the implementation on.

III. AI Importance in Games

Different methods that are used in AI learning - reinforcement, evolution-based, q-learning, curiosity-driven, etc.

- Why is it complex and important?
- What does it help to achieve?
- Talk about Halo 2 AI (and maybe TF2 bots - research more)
- Talk about how simple implementations can be much more efficient than complex learning methods

Artificial intelligence has a big place in the modern world. Robots are being created to ease human's life, machines that can beat best players in the world in most complex games such as Go (cite AlphaGo). But AI in games is not created to overcome player's abilities. It's there to enhance player's experience, to make the game more engaging and fun to play. Therefore, other difficult problems are being solved, which may not fit well with AI used in real life, but they are still very valuable. Solving AI problems using games has become pretty common nowadays and is used for many areas as a testing purpose (possible citation here).

AI for games is mainly developed to increase player's engagement and satisfaction aspects (maybe more), give the ability to set the difficulty level, create a relationship between the player and NPCs and much more (get more potential citation here). However, some games use it differently. Some games want to present players with feelings such as frustration, fear, anger (and more/possible citation). It is designers' desire to create such feelings depending on the game itself, which proves the flexibility of AI for games.

Artificial intelligence is very commonly used to create feelings alongside an atmosphere of the game. For example, in Alien: Isolation, the alien enemy is the main threat and making the player fear it to create a horrifying experience. However, atmosphere around it also plays a huge role. Moreover, specifically in this game, the AI is very complex and smart. In fact, it has two brains (citation needed). First one playing the role of what the Alien actually sees and hears and the other is having a memory of the player's position at all times, in case the player hides for a long time to create constant progression and prevent the player from playing too carefully.

Another excellent example of smart and flexible AI is Halo 2 developed by Bungie. Enemies in that game have roles of some kind: leaders, recruits and minions. These are not exact names for it, but to make it easier to distinguish while talking about. Minions are some small creatures, which are not very dangerous, because usually they walk alone or in very small groups and have little health and damage. However, they can be warned about the player or warn others of the player's position, which makes them more dangerous than they look like. Recruits, on the other, hand are much more dangerous not only because of damage and health, but also because they are lead by leaders, which they can communicate with. Moreover, leaders control several recruits and can communicate with other leaders giving them information about the player and potentially requesting help or merging, depending on each goals. The most important stuff with this is that all enemies are somewhat connected with each other, which gives them the ability to communicate and give each other information necessary to hunt the player down.

AI importance in games

- What makes AI important in games?
- What does it help to accomplish in games? Satisfaction, level of difficulty, engagement, relationship between the player and NPCs
- Has a big research area - making AI interesting and solving complex problems, which can be applied to real world problems with robots
- Potentially talk about Halo 2 AI, which made the game very engaging and fun to play - as an example
- Talk about what smart IA is like in games (video reference)

IV. Curiosity

Curiosity is a driving force for human's exploration, which consists of exploration, investigation and learning behaviours [1][2]. It makes people chase for knowledge and investigate anything new and potentially valuable. Moreover, curiosity is beneficial for people on two levels: the individual and the social [3]. The first one is represented as the "innate love of learning and of knowledge... without the lure of any profit" [4]. The social level, on the other hand, is presented as "an ingredient for enhancing personal relationships" [1].

In computational form, curiosity can be split into different designs [1]. However, in this case, we are going to look at a curious exploratory agent. It can reach high learning effectiveness in an unknown environment [1][5]. Even though the behaviour this project is going to test will be hard-coded, it gives opportunity for further learning, such as having learning algorithm like curiosity-driven instead of hard-coding. Moreover, due to curiosity being proposed as algorithmic principles [1][6][7] it enhances machines' "exploration" and allows it to own "the desire to improve the model network's knowledge about the world." [8]. It also had success in unsupervised developmental robotics [9][10].

Curiosity-driven learning in games can show some fascinating results. In [11], researchers train AI using curiosity-driven learning without extrinsic rewards and test it on dozens of games, 48 of which are Atari games. Previously, this kind of learning was using either extrinsic or intrinsic reward system, however, this paper applies no rewards for AI and yet demonstrates positive results. The research has also been using Random Network Distillation (RND), which showed a significant progress in Montezuma's Revenge [12]. It scored more than twice as high than average human, which shows potential in future development. However, it doesn't always score as high as in Montezuma's Revenge, which shows that it has still requires improvements to be used in today's games and potentially in robotics.

The way curiosity-driven learning works is that the AI tries to predict the next frame (next-state prediction / noisy-tv problem - might not be suitable)

- Why do curiosity?
- Examples of curiosity-driven behaviours
- How will it make AI look smarter?
- Challenges that occur trying to implement such behaviour
- Explain why curiosity is one of the main drivers that lead human to explore/do something
- What is smartness and how could it be measured?

V. Turing's Test

- Explain Turing's test
- Why use this testing method?
- Explain how I'm gonna test my implementation
- Briefly go over what question I'm going to use to get the participants' data
- Analyse critics regarding Turing's test and explain why I chose this method

VI. Hypotheses

The aim of this project is to implement a simple exploration behaviour and test it to see whether it makes the AI smarter. This concern is the first hypotheses of the paper. Previously mentioned testing, which requires participants to distinguish player's behaviour and AI's behaviour presents us with another hypotheses. This time we are looking if the AI's behaviour is human-like. Hypotheses 3 depends on the participants' answers - if they cannot distinguish between player and AI, it proves that the AI is human-like, which delivers positive outcome (for this paper).

These hypotheses are mainly aimed to see if exploration behaviour based on human's curiosity enhances smartness for AI in games. Due to AI primarily being used for enemies, idle states are often excluded from having "smart" behaviour. This is done in order to save memory for more important matter, such as combat. However, having a smart looking AI for walking simulators can therefore enhance player's experience in such genres. This could become a decisive factor for developers that want to create a gorgeous walking simulator using fantastic looking environment enhanced with smart and interesting artificial intelligence.

- The AI will feel smarter
- The participants won't notice the difference
- The participants won't distinguish human's behaviour and AI (which is good)

VII. Methodology

The testing of the hypotheses will be handled by presenting participants with two recordings in random order - (a) non-curious AI behaviour and player's behaviour or (b) curious AI with exploration behaviour and player's behaviour.

A. Research Artefact

For the proposed hypotheses testing the project (can I talk first person here?) will be using our team project game that is made using Unreal Engine 4 (UE4) with a few changes in the game to represent first-person walking simulator. The environment in the game will also be changed in order to more accurately generate curiosity from both AI and player perspectives. Moreover, the exploration behaviour this paper is going to test will be implemented using Behaviour Tree. The behaviour will be thoroughly tested for any possibly experience ruining errors and after recorded before gathering the data from participants. Another AI behaviour will also be recorded before the data gathering as well as human's behaviour. All the recordings will be handled by the free recording software called Open Broadcaster Software (OBS) due to it's simplicity and quality of entries.

B. Participants

Due to the need of human player's behaviour, several people will be asked to play the game and record their gameplay. This necessity does not require a lot of participants and, moreover, they will not be taking part in providing data and are not counted towards the required sample size presented in (TABLE HERE). Ideally, they will have no to little experience with such games to generate more curious nature of human. The goal for these participants will be to explore the game's environment. However, they will not be told that to avoid bias towards having unnatural curiosity behaviour, which could influence project's testing. Instead, they will have an ability to do whatever they desire. This will instead generate more natural behaviour and thought process from these participants and will benefit this project's outcome. It will be handled in the first place and all the people that will be recruited to record their gameplay will be given a consent form to sign due to university's ethics policy.

The participants that are going to provide data will likely be from different disciplines both inside and outside of Games Academy due to bigger audience variety and experience in such field. There will be two groups of participants observing different recordings of player and AI behaviours that are selected randomly. From the (INSERT TABLE HERE) it is shown that the project will need 56 participants given the effect size of 0.9. However, if the project brings more attention, sample size could be increased accordingly, giving more data to analyse.

C. Questionnaire

After the participants have viewed the recordings, they will be asked to complete a survey. The survey will provide the necessary data to analyse and later discuss the efficiency of the proposed exploration behaviour enhancing the AI's smartness. First of all, the survey will ask how often the participant plays games and whether they have played any first-person walking simulators. This will give the understanding of participant's experience with games, which might influence their insight of the research. The second part of this survey consists only of one questions asking which behaviour felt smarter in their opinion before getting the necessary data to analyse curiosity in each behaviour.

- How the hypotheses will be tested?
- Include potential questions - explain what data each question will provide
- Maybe include an example of similar test?
- Include how smartness will be measured - If the simple behaviour's score is less than exploration behaviour, it will mean that the exploration behaviour is potentially making AI look smarter

VIII. Conclusion

The conclusion goes here.

References

[1] Q. Wu and C. Miao, "Curiosity: From psychology to computation," *ACM Computing Surveys (CSUR)*, vol. 46, no. 2, p. 18, 2013.

[2] T. B. Kashdan, P. Rose, and F. D. Fincham, "Curiosity and exploration: Facilitating positive subjective experiences and personal growth opportunities," *Journal of personality assessment*, vol. 82, no. 3, pp. 291–305, 2004.

[3] T. B. Kashdan, "Curious?: Discover the missing ingredient to a fulfilling life ." 2010.

[4] G. Loewenstein, "The psychology of curiosity: A review and reinterpretation." *Psychological bulletin*, vol. 116, no. 1, p. 75, 1994.

[5] L. Macedo and A. Cardoso, "The role of surprise, curiosity and hunger on exploration of unknown environments populated with entities," in *2005 portuguese conference on artificial intelligence*. IEEE, 2005, pp. 47–53.

[6] S. Pang, S. Ozawa, and N. Kasabov, "Curiosity driven incremental lda agent active learning," in *2009 International Joint Conference on Neural Networks*. IEEE, 2009, pp. 2401–2408.

[7] C. Karaoguz, E. Potapova, D. Drix, M. Hülse *et al.*, "Curiosity driven exploration of sensory-motor mappings," in *Deliverable for the IM-CLeVer spring school at the Capo Caccia cognitive neuromorphic engineering workshop*, 2011, pp. 1–7.

[8] J. Schmidhuber, "A possibility for implementing curiosity and boredom in model-building neural controllers," in *Proc. of the international conference on simulation of adaptive behavior: From animals to animats*, 1991, pp. 222–227.

[9] Schmidhuber, "Developmental robotics, optimal artificial curiosity, creativity, music, and the fine arts," *Connection Science*, vol. 18, no. 2, pp. 173–187, 2006.

[10] F. K. Pierre-Yves Oudeyer, "Intelligent adaptive curiosity: a source of self-development," 2004.

[11] Y. Burda, H. Edwards, D. Pathak, A. Storkey, T. Darrell, and A. A. Efros, "Large-scale study of curiosity-driven learning," *arXiv preprint arXiv:1808.04355*, 2018.

[12] Y. Burda and H. Edwards, "Reinforcement learning with prediction-based rewards," https://openai.com/blog/reinforcement-learning-with-prediction-based-rewards/, 2008.

Appendix A
First appendix

Appendices are optional. Delete or comment out this part if you do not need them.