High Performance Across Two Atari Paddle Games Using the Same Perceptual Control Architecture Without Training

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ABSTRACT

Deep reinforcement learning (DRL) requires large samples and a long training time to operate optimally. Yet humans rarely require long periods training to perform well on novel tasks, such as computer games, once they are provided with an accurate program of instructions. We used perceptual control theory (PCT) to construct a simple closed-loop model which requires no training samples and training time within a video game study using the Arcade Learning Environment (ALE). The model was programmed to parse inputs from the environment into hierarchically organised perceptual signals, and it computed a dynamic error signal by subtracting the incoming signal for each perceptual variable from a reference signal to drive output signals to reduce this error. We tested the same model across two different Atari paddle games Breakout and Pong to achieve performance at least as high as DRL paradigms, and close to good human performance. Our study shows that perceptual control models, based on simple assumptions, can perform well without learning. We conclude by specifying a parsimonious role of learning that may be more similar to psychological functioning.

Keywords
Perceptual control theory · Atari games · Machine learning · Artificial agent.

1 Introduction

Gaming environments are increasingly used to develop artificial intelligence. In order to play in a gaming environment, deep reinforcement learning (DRL) agents require a long training time to learn and execute commands. The most successful model-free DRL agents DQN [21], A3C [20], and Rainbow [13] which achieved human-level of performance on Atari games, go through a trial-and-error training process for 10 days (approx. 20 Million steps). Moreover, attempts have been made at developing self-playing agents for Atari games [7,16], but none of them were able to achieve high performance. More recently, MuZero agent [31] shows that planning can achieve high performance on Atari games but it requires an extensive engineering cost involving a high computational budget. MuZero agent requires more than 2 months of training to train one agent. In this letter, we propose a new gaming Agent called PCTagent. It is arguably the first agent to achieve human-level performance on the Atari ball and paddle games by exhibiting a control architecture similar to the living organisms.

1.1 Perceptual Control Theory Modelling

Perceptual Control Theory (PCT) is a computational framework [26,29] to explain and model the behavior of living organisms based on control engineering. Within a PCT system, output (efferent) signals from each control unit within one level of a hierarchy set the goal state for input (afferent) signals at the level below. This allows actions to vary dynamically to control input ‘on the fly’, so that the planning and learning of actions is unnecessary in many
circumstances. A simple, but 'correct', architecture is necessary to achieve a good level of performance. The nervous system of a living organism requires the input functions to construct perceptual signals from the environment, and to organise these with respect to one another. This architecture may have biologically prepared foundations [25], and be further organised through verbal instruction within humans [6]; both of these pathways bypass long periods of training. A variety of PCT-based computational models have been designed that do not require training, which have emulated naturalistic behaviour within animals [4], human manual tracking [24], human crowd behaviour [19], flyball catching [18] and robotic devices [37], [3]. However, there is little published evidence using established benchmarks within commonly used hardware or modelling environments to compare with approaches that do require training for the learning of actions. This was the aim of the current study.

1.2 Existing AI Methods for Arcade Games

Atari arcade games have been benchmarked primarily using model-free RL algorithms. DQN [21] utilises deep neural network (DNN) to train Q-learning policies by incorporating replay experience and target networks. Several attempts have been made to extend DQN by incorporating bias correction, e.g. DDQN [33], and by prioritising experience replay [30] by architectural modifications [34], and distributional value learning [8]. Some attempts have been made to improve performance by data collection, which increases the cost of environment steps beyond 200 million [2, 20]. Agents developed on proprioceptive inputs [12, 14], model images without using them for planning [17, 23], or combine the benefits of model-based and model-free approaches [17, 22]. Most model-based agents with image inputs have thus far been limited to relatively simple control tasks [10, 35].

SimPLe agent [16] learns a video and predicts a model in pixelated data format and utilises its predictions to train a proximal policy agent [32]. The model tracks and establishes prediction based on four consecutive frames and incorporates discrete latent variable as an input. The authors evaluate SimPLe on a subset of Atari games for 400k and 2M environment steps, after which the rewards decreased, hence the model over-fitted the environment. As a direct contrast to the above designs, we have used perceptual control theory as a computational framework to show a competitive performance with no training. PCTagent was built on a single GPU Core i7 laptop, for the paddle operated game environment, within which it outperforms top single-GPU Atari agents Rainbow [13] and IQN [8] which rest upon years of model-free RL research [9].
Table 1: Ball and Paddle games results of different ML Agents

| Agent Name  | Best Score | Training Frames |
|-------------|------------|-----------------|
| DQN         | 401        | 21              |
| DBA3C       | 301        | 21              |
| SimPLe      | 16.4       | 5.2             |
| RADAR       | 600+       | 21              |
| Rainbow     | 120        | 21              |
| IQN         | 79         | 21              |
| DreamerV2   | 312        | 21              |
| Human World record | 864 | 21 |
| Random      | 2          | -20             |
| **PCTagent (Ours)** | **862** | **18*** |

*Frameskip version

2 Method

2.1 A PCT Agent and Model

PCTagent was developed based on four sub-system hierarchical model of behavior, as shown in Fig. 2 and is available to download under GPL 1. The design of a PCT agent is based on a systematic logical analysis of the sensors and effectors of a system, and the performance requirements of the task, that can be specified as an algorithm [11]. Within the Breakout scenario, the sensor can estimate the distance between the paddle and ball, which needs to be controlled at zero to perform the task. Yet the effector only commands the rate of button press left or right. Therefore, a hierarchy was constructed that bridges between the control of button press at the bottom level and the control of paddle-ball distance at the top level. Two intermediate levels were required. The full architecture can therefore be described as follows. The top level of PCTagent controls the visual perception of the distance (D) to be maintained between the paddle and a moveable ball in the game environment, as shown in Fig. 1(a)(b). Within Fig. 2, the error (e1) in the top sub-system sets the reference value (R2) for the direction control left or right of the paddle, which is compared to the sensed direction of the paddle (MD), to generate an error (e2) that sets the reference value (R3) for the next level down. The next level down perceives the the position of the paddle (Px) and compares this to the reference value for movement (R3). Error in this system (e3) sets the reference value (R4) for the left or right button press (BP), and in turn the error of this system (e4) is transformed to a frequency of button press which determines how far left or right user has to move to hit the ball. An inherent embedded property of button press sub-system is the control of the velocity at which the paddle has to move to catch the ball. Within this sub-system, rate of button press is counted by an integrator, which has a limit (currently set to 3), upon reaching max, the integrator resets and reverts to its previous position. Each level of the model contains a k parameter which is the gain of each unit. The gain values for this PCT agent were all set to the value of 1 because this required no a priori assumptions regarding their optimal value.

2.2 ALE Environment and Image Processing

We used the Arcade Learning Environment (ALE) as a platform to empirically assess the performance of our PCTagent. ALE provides an interface for different Atari 2600 game environments which are challenging and engaging for humans. ALE serves as a benchmark environment for the evaluation of AI agents. As an input to our PCTagent we obtained raw Atari frames, which are 210X160 (height,width) pixel image with a 128 color representation. To make the game computationally efficient, we reduced the input matrix dimensionality by first converting it to binary and then cropping it to obtain a 100X132 region, capturing only the playing area. We do not require any specific square size images, mostly required by 2D convolution algorithms. The tracking of the ball and the paddle were done using simple contour detection function of OpenCV2 module running under Python 3.8.

3 Atari Paddle Games Experiments

First we present our PCTagent’s performance results and a comparison of this performance with other state-of-the-art agent as tabulated in Table-1. In Table-1, it can be seen that all of the machine learning game playing agents require

[1]https://github.com/PCT-Models/PCTagent_Breakout_Atari
High Performance on Atari using PCTagent

Figure 2: Hierarchical PCT model for ball and paddle Atari Games.

millions of frames for training for weeks, whereas since PCTagent does not require any training, hence was ready to play instantly. PCTagent’s highest score for Breakout and Pong was 862 and 18, respectively.

Paddle games e.g. Breakout and Pong were used to evaluate the performance of our training free PCTagent. The games and PCTagent were run on an Intel Core-i7 single GPU machine with AMD Radeon RX 640 graphics card. Both Pong and Breakout were tested for different Open Gym environment modes i.e. with/without frame skipping and deterministic mode. The games were ran for 500 episodes and scores data were collected as shown in Fig. 3. In Breakout, a negative reward of -1 for each life lost and in Pong a -1 reward for opponent’s successful score was set. It is evident from the results (shown in Fig. 3) that in Breakout it is possible to achieve an average highest score of 400+ and in Pong to win the game with a margin of 5-6 points, at no prior training costs. In Pong, the noframeskip mode resulted in all wins - scores of 21, hence frameskip mode was used during data collection. A significant noise was introduced in the PCTagent when the game were stuck in one position. In the case of Breakout this usually happened in the end (noframeskip mode) when one or two bricks were left to hit, which resulted most of the time in losing a life.

4 Conclusion

We produced one controller based on PCT and tested it, without training, on two different Atari paddle games. Its performance matched or exceeded that of published benchmarks from existing reinforcement and deep learning models. These findings complement earlier studies demonstrating the high performance of PCT controllers within robotics and
other areas of research [37], [3]. Indeed, the findings are particularly consistent with an earlier comparison between a PCT controller and an LQR controller for an inverted pendulum robot [15]. This PCT controller required minimal tuning and its performance metrics were superior.

PCT controllers can provide a robust control solution across environments with no training because they have no need to learn their actions. Instead, they achieve control by varying their outputs on-the-fly to control their inputs by acting against unpredictable disturbances (e.g. turbulence, rough ground), unlike reinforcement models. The closed-loop PCT design emulates control systems in nature, which also do not need to learn specific behaviours to operate effectively and efficiently [36]. The choice of input specifications and their hierarchical organisation can be made through a systematic analysis of the sensors, effectors and the task requirements rather than through learning, or inferences made by the researcher [11]. This begs the question of whether reinforcement learning accounts for human skills or whether PCT provides a more accurate model - an architecture of ‘priors’ proposed to forge future advances in AI [5]. Importantly, PCT controllers can further improve performance through training if required. The learning algorithm specified in PCT - reorganisation - uses random-walk learning to optimise the parameters (e.g. gains) and functions (e.g. specification
of inputs that co-vary with target velocity) within a PCT architecture. This is a future direction for computational modelling using PCT.

References

[1] Mohammad Babaeizadeh, Chelsea Finn, Dumitru Erhan, Roy H Campbell, and Sergey Levine. Stochastic variational video prediction. arXiv preprint arXiv:1710.11252, 2017.

[2] Adrià Puigdomènech Badia, Bilal Piot, Steven Kapturowski, Pablo Sprechmann, Alex Vitvitskyi, Zhaoan Daniel Guo, and Charles Blundell. Agent57: Outperforming the atari human benchmark. In International Conference on Machine Learning, pages 507–517. PMLR, 2020.

[3] Joseph W. Barter and Henry H. Yin. Achieving natural behavior in a robot using neurally inspired hierarchical control. bioRxiv, 2021.

[4] Heather C Bell, Greg D Bell, Jeffrey A Schank, and Sergio M Pellis. Evolving the tactics of play fighting: Insights from simulating the “keep away game” in rats. Adaptive Behavior, 23(6):371–380, 2015.

[5] Yoshua Bengio, Yann Lecun, and Geoffrey Hinton. Deep learning for ai. Communications of the ACM, 64(7):58–65, 2021.

[6] Carla Brown-Ojeda and Warren Mansell. Do perceptual instructions lead to enhanced performance relative to behavioral instructions? Journal of Motor Behavior, 50(3):312–320, 2018.

[7] Silvia Chiappa, Sébastien Racanière, Daan Wierstra, and Shakir Mohamed. Recurrent environment simulators. arXiv preprint arXiv:1704.02254, 2017.

[8] Will Dabney, Mark Rowland, Marc Bellemare, and Rémi Munos. Distributional reinforcement learning with quantile regression. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 32, 2018.

[9] Meire Fortunato, Mohammad Gheshlaghi Azar, Bilal Piot, Jacob Menick, Ian Osband, Alex Graves, Vlad Mnih, Remi Munos, Demis Hassabis, Olivier Pietquin, et al. Noisy networks for exploration. arXiv preprint arXiv:1706.10295, 2017.

[10] Danijar Hafner, Timothy Lillicrap, Jimmy Ba, and Mohammad Norouzi. Dream to control: Learning behaviors by latent imagination. arXiv preprint arXiv:1912.01603, 2019.

[11] Benjamin Hawker and Roger K Moore. Robots producing their own hierarchies with dosa; the dependency-oriented structure architect. UK-Robotics and Autonomous Systems (RAS) Network, pages 66–68, 2020.

[12] Mikael Henaff, William F Whitney, and Yann LeCun. Model-based planning with discrete and continuous actions. arXiv preprint arXiv:1705.07177, 2017.

[13] Matteo Hessel, Joseph Modayil, Hado Van Hasselt, Tom Schaul, Georg Ostrovski, Will Dabney, Dan Horgan, Bilal Piot, Mohammad Azar, and David Silver. Rainbow: Combining improvements in deep reinforcement learning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 32, 2018.

[14] Juan Camilo Gamboa Higuera, David Meger, and Gregory Dudek. Synthesizing neural network controllers with probabilistic model-based reinforcement learning. In 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 2538–2544. IEEE, 2018.

[15] Thomas Johnson, Zhou Siteng, Wei Cheah, Warren Mansell, Rupert Young, and Simon Watson. Implementation of a perceptual controller for an inverted pendulum robot. Journal of Intelligent & Robotic Systems, 99(3-4):683–692, 2020.

[16] Lukasz Kaiser, Mohammad Babaeizadeh, Piotr Milos, Blazej Osinski, Roy H Campbell, Konrad Czechowski, Dumitru Erhan, Chelsea Finn, Piotr Kozakowski, Sergey Levine, et al. Model-based reinforcement learning for atari. arXiv preprint arXiv:1903.00374, 2019.

[17] Gabriel Kalweit and Joschka Boedecker. Uncertainty-driven imagination for continuous deep reinforcement learning. In Conference on Robot Learning, pages 195–206. PMLR, 2017.

[18] Richard S Marken. Optical trajectories and the informational basis of fly ball catching. 2005.

[19] Clark McPhail, William T Powers, and Charles W Tucker. Simulating individual and collective action in temporary gatherings. Social Science Computer Review, 10(1):1–28, 1992.

[20] Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In International conference on machine learning, pages 1928–1937. PMLR, 2016.
[21] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *nature*, 518(7540):529–533, 2015.

[22] Anusha Nagabandi, Gregory Kahn, Ronald S Fearing, and Sergey Levine. Neural network dynamics for model-based deep reinforcement learning with model-free fine-tuning. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 7559–7566. IEEE, 2018.

[23] Junhyuk Oh, Xiaoxiao Guo, Honglak Lee, Richard Lewis, and Satinder Singh. Action-conditional video prediction using deep networks in atari games. *arXiv preprint arXiv:1507.08750*, 2015.

[24] Maximilian G Parker, Andrew BS Willett, Sarah F Tyson, Andrew P Weightman, and Warren Mansell. A systematic evaluation of the evidence for perceptual control theory in tracking studies. *Neuroscience & Biobehavioral Reviews*, 112:616–633, 2020.

[25] Frans X Plooij. The phylogeny, ontogeny, causation and function of regression periods explained by reorganizations of the hierarchy of perceptual control systems. In *The Interdisciplinary Handbook of Perceptual Control Theory*, pages 199–225. Elsevier, 2020.

[26] W. T. Powers. *Behavior: The control of perception*. Aldine Chicago, 1973.

[27] William T Powers, RK Clark, and RL McFarland. A general feedback theory of human behavior: Part ii. *Perceptual and Motor Skills*, 11(3):309–323, 1960.

[28] William Treval Powers. Living control systems iii: The fact of control. 2008.

[29] William Treval Powers, Robert K Clark, and RL McFarland. A general feedback theory of human behavior: Part i. *Perceptual and motor skills*, 11(1):71–88, 1960.

[30] Tom Schaul, John Quan, Ioannis Antonoglou, and David Silver. Prioritized experience replay. *arXiv preprint arXiv:1511.05952*, 2015.

[31] Julian Schrittwieser, Ioannis Antonoglou, Thomas Hubert, Karen Simonyan, Laurent Sifre, Simon Schmitt, Arthur Guez, Edward Lockhart, Demis Hassabis, Thore Graepel, et al. Mastering atari, go, chess and shogi by planning with a learned model. *Nature*, 588(7839):604–609, 2020.

[32] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

[33] Hado Van Hasselt, Arthur Guez, and David Silver. Deep reinforcement learning with double q-learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 30, 2016.

[34] Ziyu Wang, Tom Schaul, Matteo Hessel, Hado Hasselt, Marc Lanctot, and Nando Freitas. Dueling network architectures for deep reinforcement learning. In *International conference on machine learning*, pages 1995–2003. PMLR, 2016.

[35] Manuel Watter, Jost Tobias Springenberg, Joschka Boedecker, and Martin Riedmiller. Embed to control: A locally linear latent dynamics model for control from raw images. *arXiv preprint arXiv:1506.07365*, 2015.

[36] Henry Yin. The crisis in neuroscience. In *The Interdisciplinary Handbook of Perceptual Control Theory*, pages 23–48. Elsevier, 2020.

[37] Rupert Young. A general architecture for robotics systems: A perception-based approach to artificial life. *Artificial life*, 23(2):236–286, 2017.