Towards Adaptive Deep Reinforcement Game Balancing*

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Abstract: The experience of a player regarding the difficulty of a video game is one of the main reasons for he/she decide to keep playing the game or abandon it. Effectively, player retention is one of the primary concerns related to the game development process. However, the experience of a player with a game is unique, making impractical to anticipate how they will face the gameplay. This work leverages the recent advances in Reinforcement Learning (RL) and Deep Learning (DL) to create intelligent agents that are able to adapt to the abilities of distinct players. We focus on balancing the difficulty of the game based on the information that the agent observes from the 3D environment as well as the current state of the game. In order to design an agent that learns how to act while still maintaining the balancing, we propose a reward function based on a balancing constant. We require that the agent remains inside a range around this constant during the training. Our experimental results show that by using such a reward function and combining information from different types of players it is possible to have adaptable agents that fit the player.

1 INTRODUCTION

In video game, the *gameplay* portrays an important role to the success of a game. Thus, arguably, even if a game has the most realistic audiovisual features or the most fanciful story, but it contains challenges unsuitable to the player's ability, this may affect his experience, making him abandon the game.

Thus, issues related to the gameplay refer to how the game interacts with the player, such as, the game's challenges, objectives, rules, and so on (Southey et al., 2005). Many efforts have been made to yield adjustable games such that the player does not get frustrated by a very difficult game, or bored, when the game is too easy. Commonly, this problem is tackled by creating a finite number of difficulty levels (Olesen et al., 2008) that the players must select according to their beliefs on which one better fits. Nevertheless, this is possibly an ineffective solution as the player may have intermediate skills between these classes or because he is constantly learning (or forgetting) skills, or still because the player may have a wrong vision of its own abilities (Missura and Gärtner, 2009).

Thus, terms such as difficulty adjustment (Hunicke, 2005; Missura and Gärtner, 2009), adaptive game (Spronck et al., 2006) and dynamic game balancing (Andrade et al., 2006) are receiving a great attention in the games' industry. Particularly, the topic of dynamic game balancing refers to the process of automatically changing behaviors, parameters, and/or elements of the scenarios in a video game in real-time, to match the game to the ability of a specific player (Andrade et al., 2005). For a long time, most of the effort to yield balanced games were based on creating specific heuristics and/or probabilistic methods that would hardly adapt to different games or players with diverse abilities (Silva et al., 2015; Hunicke, 2005).

Based on this motivation, we propose a strategy where the non-player characters, which can certainly influence the gameplay, have the ability to *learn how to act* and leverage the game balancing. By going in this direction, we expect that they can match the human player performance, whatever the game is, and consequently make the player has more fun and stick to the game.

To achieve similar game-based goals, previous works have taken advantage of Machine Learning methods, focusing on providing artificial agents with the ability of learning from experience without being explicitly programmed (Mitchell, 1997; Michalski et al., 2013). Other approaches follow a semi-automatic analysis of the playability of a game (Southey et al., 2005), recognizing the level of knowledge the player has to configure opponents (Bakkes

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et al., 2009) and new environments according to the player's progress(Lopes et al., 2018).

Other researchers have attacked the same problem by recognizing the type of player, followed by a comparison to groups of similar players and, finally, configuring the game according to the mapped characteristics (Missura and Gärtner, 2009). However, it may be difficult to fit the player to a group of other players, as human behavior presents quite singular and unique traits (Charles et al., 2005).

There are still other approaches that focus on creating adaptable agents that directly interacts with the environment, taking advantage of Reinforcement Learning techniques (Sutton et al., 1998). In this case, the agent receives the current state of the environment and a reward value aiming at learning the policy it should follow. Previous work(Andrade et al., 2005) has followed this approach by using the classical Q-learning algorithm (Watkins and Dayan, 1992). Nevertheless, value-based methods such as Q-learning may face difficulties to deal with continuous space and may converge slowly, as they are not directly optimizing the policy function.

In this work we propose a NPC-agent that does not need a representative model of the player to adapt to him, and whose policy is directly induced from how the agent observes the game. To achieve that, we designed a reward function that is based on a game-balancing constant and introduce it into the Proximal-Policy-Opmitization (PPO) (Schulman et al., 2017) algorithm, a reinforcement learning method that directly optimizes the policy using gradient-based learning. In order to tackle the complexity of the environment, the PPO implementation we selected follows a Deep Reinforcement Learning approach (Mnih et al., 2015). In this way, we can also benefit from the remarkable results that other game-based problems have recently achieved (Mnih et al., 2013; Silver et al., 2016; Lample and Chaplot, 2017). We take advantage of the Unity ML-Agents Toolkit (Juliani et al., 2018) to implement the graphical environments and to run the PPO algorithm. Experimental results show that we are able to devise adaptable agents, at least when facing other non-human players.

2 RELATED WORK

The challenge of balancing the game refers to the ability of a game to modify or adjust its level of difficulty according to the level of the user so that he can be content with the game. This includes avoiding that the player get stressed or bored when playing the game due to very difficult or easy situations (Csikszentmihalyi and Csikszentmihalyi, 1992). In fact, (Andrade et al., 2006) has showed that satisfaction and balance are quite related, by asking some players to answer a series of questions after experiencing a fighting game.

To achieve game balancing, previous work has focused on trying to add new content (environments, elements, obstacles, etc.,) regarding the abilities of the player while others has sought to create intelligent agents capable of facing the player but without hindering their possible success (Bakkes et al., 2012). Examples of the first group includes (Bakkes et al., 2014) and (Hunicke, 2005), which tries to modify the environment or adding new elements, but knowing beforehand how to represent the behavior of the player within the game.

Regarding the second group, in (Missura and Gärtner, 2009), the authors tried to create an automatic adjustment by first identifying the level of the player and then fitting him into a specific group (Easy, Medium or Difficult). The goal is to include a new player inside one of these groups so that their opponents are easier or more difficult to confront. That work sees the identification of the type of player as a fundamental issue to have balanced games. Our work aims to avoid creating abstractions and representations of the player, as this is sometimes difficult to observe beforehand. Instead, we focus on representing the current state of the game to determine the decision-making policy of the agent against his opponent.

Meanwhile, (Silva et al., 2015) uses a heuristic function to determine the performance of the player when facing his enemies during the game and, according to it, the difficulty of the game is increased or decreased. Regarding the use of Reinforcement Learning (RL), which is the Machine Learning technique most used to game-based issues, (Andrade et al., 2006) adopted RL to teach a virtual agent to imitate the player. After that, the agent is further trained to balance the difficulty of the game. The work presented in (Andrade et al., 2005), unlike to the previous one, only used RL to teach the agent to fight and the balancing is achieved by a heuristic function tuned according to the abilities of the player. We do not intend to teach the agent to imitate a player, but, instead, we aim at devising an agent that learns altogether how to play the game *and* how to adapt to the player.

3 REINFORCEMENT LEARNING

In this work we rely on Reinforcement Learning (Sutton et al., 1998) to make the agent learn how to act to achieve game balancing. We benefit from the Unity

ML-agents (Juliani et al., 2018) to implement the game environment coupled with the RL algorithms' implementation. In this section we overview both these components of our work.

Reinforcement Learning aims at teaching the agent to make decisions when facing a certain situation through trial and error. When learning, the agent receives an stimuli in the form of a reward so that it can evaluate if the chosen action was good for the decision making or not.

A RL task can be formally described as a Markov Decision Process (MDP) (White III and White, 1989). Thus, at each time step t of the decision making process, the environment is represented by a state $s \in \mathcal{S}$(the set of states), and the agent may choose an action $a \in \mathcal{A}$(the set of actions) that is available in the state s. A transition function (possibly non-determinisic) $\mathcal{T}\nabla$ defines indicates the state s' that the agent will land on in the instant $t+1$, given it has taken action a in t when it was in the state s. After going from the state s to the state s' because of the action a, the agent receives an immediate reward $R_a(s,s')$. A discount factor γ indicates how the future rewards matters compared to the current one.

The overall goal is to find a *policy* $\pi^* = argmax_a \mathbb{E}[R|\pi]$ that maps from states to actions in order to maximize the accumulated reward R (obtained from the environment in every rollout of a policy) of all states(Sutton et al., 1998).

Proximal Policy Optimization. As the RL method, in this work we follow the *Proximal Policy Optimization* algorithm due to its recent success on handling a number of game problems (Schulman et al., 2017). It is a policy search-based method largely inspired on the Advantage Actor Critic (A2C) framework (Mnih et al., 2016). The Advantage Actor critic method relies on a gradient estimator coupled with an advantage function $\hat{A}_t = -V(s_t) + r_t + \gamma r_{t+1} + \cdots + \gamma^{T-t+1} r_{T-1} + \gamma^{T-t} V(s_T)$ such that $\hat{g}L^{PG(\theta)} = \hat{\mathbb{E}}[\nabla_\theta \log \pi_\theta(a_t|s_t)A_t]$. The estimator of the advantage function runs the policy for T timesteps instead of waiting to the end of the episode to collect the reward, and uses those collected samples to update the policy.

Here is where the Critic comes, to estimate the advantage function value. Within Deep Reinforcement Learning, we have a neural network to estimate $\pi(s,a,\theta)$ (the actor) and another one to estimate the advantage function (the critic), where they possibly have shared parameters.

Algorithm 1 reproduces the PPO algorithm from (Schulman et al., 2017). Note that L represents either a clipped version or a KL-penalized version of the objective function differentiated through the estimator $\hat{g}$.

Algorithm 1: PPO top-level algorithm, Actor-Critic style, as presented in (Schulman et al., 2017).

for $iteration = 1, 2, ...$ **do**
  for $actor = 1$ **to** N **do**
    Run policy $\pi_{\theta_{old}}$ in environments for T timesteps;
    Compute advantage estimates $\hat{A}_1, ..., \hat{A}_T$;
  end
  Optimize surrogate L wrt θ, with K epochs and minibatch size $M \leq NT$;
  $\theta_{old} \leftarrow \theta$
end

4 BALANCING GAMES WITH DEEP RL AND A BALANCING CONSTANT

This work aims at creating a game agent with two implicit goals that should be targeted at the same time: learning how to play a game and, at the same time, learning how to go keep up with the player to maintain the game balanced. To that, we build a reinforcement learning task and use the PPO algorithm to solve it due to one main reason: our task contemplates a continuous space and policy search is more appropriate to tackle this kind of environment. Moreover, PPO has succeeded in a number of other game-based tasks (Schulman et al., 2017). In this section we bring the details of our contributions.

Reward Function. A key component of an RL task is how we reward or penalize the learner according to his actions in the environment. To tackle the balancing game problem, the reward function must envision the behavior of the agent in the game environment (for example, how to move, or how to fight) along with the balancing itself (how to not bw much worse or much better than the player). Thus, we propose a game-based reward function that includes a balancing constant aiming at pointing out how the agent can be a fair opponent to the player. In this way, he will have some implicit knowledge on how far (or near) he is from the desired balanced state and, if he is within it, how he should behave in such a state.

Balancing Constant (BC). The balancing state refers to the moments of the game that a skill difference remains in a certain range(1). The intuition behind this is that in such a state, the agent is not

that easy to confront or that difficult to overcome by the player. Consequently, the balancing constant is a value that helps our function to achieve the desired behaviour. In other words, this constant means the maximum skill difference between the agent and the player.

$$0 \leq \Delta Skill \leq BC \tag{1}$$

BC-Based Reward Function (BCR). Nevertheless, by using the BC in our reward function it is possible to distinguish two additional situations when the agent is not in a balanced state, *i.e.*, the BCR can identify in which situation the agent is and, according to it, to provide a reward value to stimulate the desired learning (equation 2). The three reward situations are as follows:

Subjugated Punishment (SP), defined as $\Delta Skill < 0$: In this case, the reward value is directly proportional to the inability of the agent to represent an obstacle to the player, i.e., the more docile the agent is the more it will be punished.

Conservation Reward (CR), defined as , $0 \leq \Delta Skill \leq BC$: In this case, the reward value represents a compensation for maintaining the degree of competition within the desired range of the BC, which in turn encourages the agent to reach the limit of equilibrium.

Rebellious Punishment (RP), defined as $BC < \Delta Skill$. This is an inverse retaliation to the Subjugated Punishment case, obtained by overcoming the BC limit that the agent can have with respect to his opponent.

$$BCR(\Delta Skill) = \begin{cases} \frac{\Delta Skill}{Skill_{max}}, & if \quad \Delta Skill < 0 \\ \frac{\Delta Skill}{BC}, & if \quad 0 \leq \Delta Skill \leq BC \\ -\frac{\Delta Skill - BC}{Skill_{max} - BC}, & if \quad BC < \Delta Skill \end{cases} \tag{2}$$

We can see in the figure 1 that $BCR(\Delta Skill)$ is a piece-wise function that reflects our idea of the three possible major cases that the agent may attained during training. Thus, if the agent is very distant from the range of balancing, consequently, it will receive an even greater punishment; on the other hand, if it gets to be within the balancing state, it is stimulated to reach the limit of the range.

BC-Based Balancing Metric (BCM). The BCM (equation 3) is a measure that allows for evaluating the percentage of times that an agent is in one of the states reflecting the three situations mentioned above: Unbalanced by Subjugate, Balanced, or Unbalanced by Rebellious.

$$BCM = \frac{T_B}{T_{US} + T_B + T_{UR}} \tag{3}$$

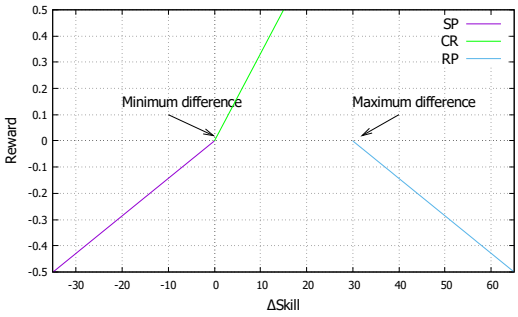


Figure 1: The BC-Based Reward Function with $BC = 30$ and $Skill_{max} = 100$.

Our hypothesis is that as a base case of balancing, the player can perform different actions that may cause the agent to receive a punishment for not keeping the game within the BC interval, so the agent must perform an action to control this situation. Conversely, an unbalanced state will make the agent to execute an action to move the game to a balanced state, as shown in figure 2.

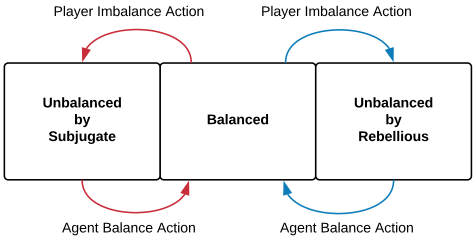


Figure 2: Minimal Agent Balancing Interaction.

5 EVALUATION

In this section we present our test scenario and show the results we have obtained with the game balancing method we proposed here.

5.1 Unity ML-Agents Toolkit

To produce the game environment scenarios and run the RL algorithm, we rely on The Unity ML-Agents Toolkit (Juliani et al., 2018). It is a free-source toolkit that allows the development of virtual environments to serve as training scenarios for intelligent agents, using machine learning algorithms based on TensorFlow (Abadi et al., 2016). The toolkit contains three high-level key components: (1) the Learning Environment, containing all the elements of the game that are part of the Unity, (2) the Python API, composed of the training algorithms, and (3) the External Communicator, connecting the Python API to the Unity.

The toolkit has a component called Brain which contains three elements of the RL task: (1) the **Observation**, which is the information provided by the agent about the environment, either in a numerical format (floating-point number vector) or visual (images taken by the cameras linked to the agent); (2) the **Action**, represented as a vector of continuous or discrete actions; and (3) the **Reward**.

Furthermore, a set of extensible examples using different RL algorithms are available in the toolkit. The Proximal Policy Optimization (PPO) (Schulman et al., 2017) implemented in the toolkit has the possibility of propagating its performance with the Intrinsic Curiosity Module (ICM) or even with a Long-Short-Term Memory model (LSTM). As we previously mentioned, we focus on creating an intelligent agent based on the PPO algorithm.

5.2 Test Game Scenario

We evaluate our game balancing method in an environment similar to the commercial game Capcom Street Fighter, inspired by (Andrade et al., 2006). The game consists of the confrontation of two entities (the agent and the player), whose objective is to defeat the opponent through physical attacks. The game ends when one of them makes the other to be lifeless or when the time of 100 seconds has passed. In this last case, the winner is the player that has more life points in the end of the game. This game is based on a 3D environment, like most of the current video games

5.3 Player Simulation

To simulate the behavior of players with distinctive nature, we created two types of enemies with different abilities that are going to confront our learner agent, as follows:

- **Defensive Simulation:** This programmed enemy emulates the behavior of a player whose goal is to win by a minimum difference. Thus, he adopts a defensive posture to avoid taking any damage while still maintaining his advantage.
- **Aggressive Simulation:** The behavior of this other type of emulated player differs from the previous one because this one tries to win with the maximum possible difference, *i.e.*, it will try to attack all the possible times to generate the greatest damage in our learner agent.

5.4 Skill Study

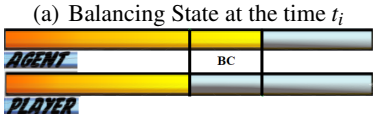
Naturally, as we work with a fighting game, we consider adequate to measure the balance of the game by computing the difference in the life health score of the agent and the player (Equation 4). Therefore, the balancing state is assumed as long as the agent maintains a difference within the BC interval (Equation 5).

$$\Delta H = H_{Agent} - H_{Player} \tag{4}$$

$$0 \leq \Delta H \leq BC \tag{5}$$

In this way, our objective is advising the agent to maintain a life difference not bigger than the BC along the game time, as shown in Figure 3.

(a) Balancing State at the time t_i



(b) Balancing State at the time t_{i+1}

Figure 3: Persistence of the BC throughout the game with $BC = 30$.

5.5 Observation Parameters (State) and Actions

The reinforcement learning task requires that we abstract the environment into the state representation so that the agent can make a decision regarding their actions. Figure 4 illustrates the learning loop of our study game. Thus, as we tackle a fighting game, we represent the observation of the current state of the game using the following information:

- Information related to the physical space: distance between the learner agent and the player.
- Information related to the balancing constant: the value of the difference between the health of the agent and the health of the player and the type of reward the agent receive (subjugated or rebellious punishment, or conservative reward.
- Information related to the actions: the last action of the agent and the player, as well as a discrete value that tells us if the player has changed action since the last observation.

All of these values are normalized between -1 and 1, as a recommendation of the Unity plugin for better performance.

Concerning the actions, both agents can Move (Walk forward, Walk Backward), Duck and Attack (Kick, Punch).

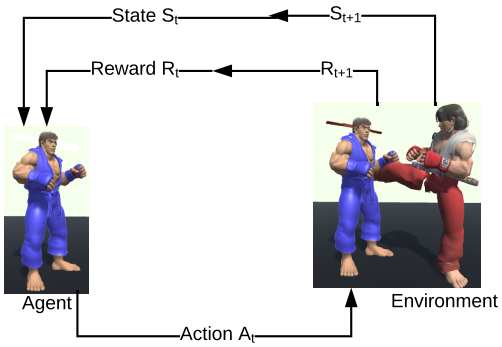


Figure 4: RL process focused on games.

5.6 Experimentation

The experimentation process was carried out using three values of BC (20,30 and 40), which the agent uses as a limit of their ability. As we described earlier, we created two different types of emulated players to face our agent and allows him to train, aiming at obtaining:

- Two different types of agents, namely an aggressive and a defensive one, which fight and behave within the boundary of the BC when confronted with their same type of emulated agent.
- A third type of agent (Mixed Agent) that is trained with the two different types of emulated players. Thus, we would like to demonstrate that given the experience of facing different types of players, the agent can adapt to them when it is necessary.

We change some default parameters of the PPO implementation to improve the training. The first one is the β parameter, responsible for defining how the agent explores its actions. The greater is this value, the more at random the agent chooses its actions and, therefore, the more it will explore the action space during its training. This variable is directly related to the strength of the entropy regularization. We set this variable as $(1e-5)$ so that our agent experiences new possibilities and applies the learned model to reach the goal. During the experiments, smaller values make the agent learn only a certain number of actions that, while helped him reach part of his goals, were very repetitive. The learning rate parameter was also adjusted with the same intent as the β parameter. We set this variable to be $(5e-4)$ so that the agent maintains an equilibrium between not learning too fast or delaying too much by exploring new actions. The other parameters were kept with the default values of the plugin.

We created 9 independent copies of the scene to accelerate the training by working together to find a better policy. All of them have the emulation of one type of the player's behavior, except for the mixed agent training that had 4 passive and 5 aggressive emulations. The figure 5 shows us how each of them is independent from each other: some of them are in a balanced state (green platforms) while others have not reached the best policy.

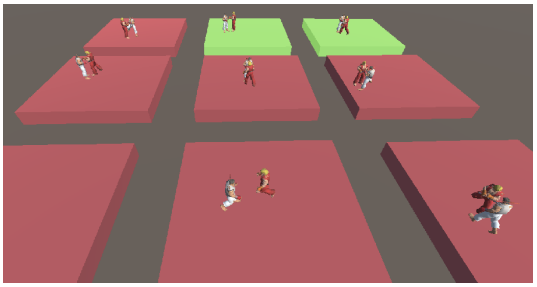


Figure 5: Initial stage of the training process with 9 scenes in parallel.

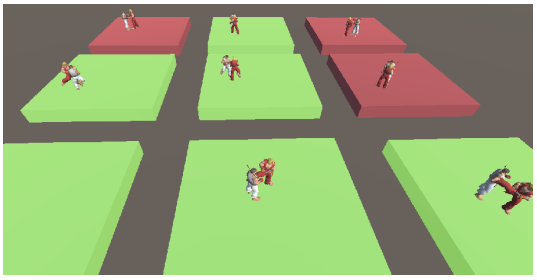


Figure 6: Intermediate stage of the training process with 9 scenes at the same time.

5.7 Results

Based on our experiments, we start by indicating that after 500k steps the agent tends to continuously improve its policy, generating a greater reward, as shown in Figure 7 and many of the 9 scenarios manage to balance the game (Figure 6). Hence, in the case of the agents that learn from only one type of player, we observed that the agent who faces aggressive emulation did not take long to learn the (defensive) policy and then maintain it until the number of iterations is finished. Because the emulation is so aggressive, the agent learned that it is better to defend itself and maintain a minimum difference than trying to reach a $\Delta Skill = BC$ or higher (be more aggressive). Unlike the other, he tries to be more aggressive and his training goes more slowly since the agent must also learn how to attack (to reach the balancing state) and defend himself (to stay within the balancing state).

Figure 7 shows how the agent that learns with the mixed simulated types of players has an intermediate reward gain between the other two cases. This is likely due to the fact that he must learn how to behave when facing two different strategies of its opponents, consequently, he has more things to learn. Regarding the balancing constant values, the results show that

when the BC is higher, the agent is able to maintain his skill difference with respect to the player into the interval of balancing. He is also able to remain in the balanced state even when he suffers some damage by the opponent because there is still some life difference between them.

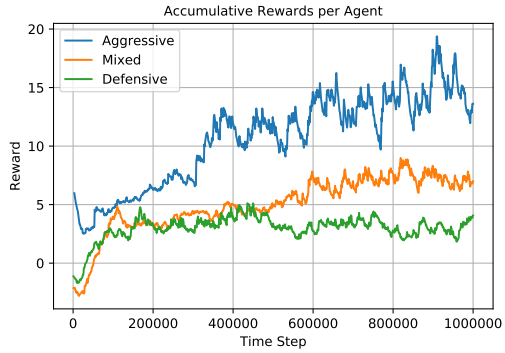


Figure 7: Accumulated Reward throughout the training.

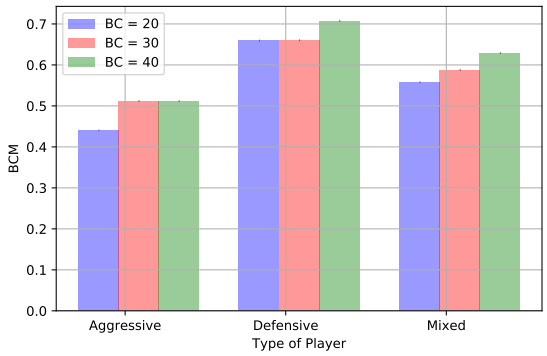


Figure 8: Evaluation on BC-Metric.

Conversely, it is quite hard to preserve the equilibrium when the BC is small because any wrong action by the agent could take it to any of the unbalanced states. For example, we can observe in Figure 8 when the agent has a $BC = 20$ and he needs to fight against an aggressive player, the former spends a little less than 50% of the time in our target balanced state.

Finally, our BC-Metric showed 3 interesting points. First, the agent remains at least 50% of time in the state of balancing in all cases, except when $BC = 20$ as we described before. Second, we see some evidence to confirm the hypothesis about a small value of BC, showing that in this case, it is difficult to stay in the balanced state with a narrow range. Third, the results show that by offering new experiences through the mixed agent, it is able to achieve a better decisions because he learns a new type of behavior that one style alone cannot offer, In this case, the results exceed 50% of BC-Metric, even with a $BC = 20$, as exhibited in the Figure 8.

6 CONCLUSIONS

Game balancing faces the complex challenge of adapting the virtual characters to the same (or a higher) level as the player. In this work, we contributed with a deep reinforcement learning strategy that aims at reaching such a balancing through the reward function. To that, we designed a function that makes use of a balancing constant to limit and measure the behavior of the agent. By training the agent with such a function, we were able to not only limiting the agent to behave like the player (when the BC is zero), but we also gave him the possibility of stimulating himself to learn the games' actions, so that it is still a good adversary to the player. With the experimental results, we could observe that the agent stays as long as possible in a balanced state (at least 50% of the game). Furthermore, we could see that it can learn new ways of acting when confronting different styles of players.

As future work, we intend to deeply explore the adaptability of the agent, by composing rewards that point out to more granular aspects such as resistance and stamina, and gathering the results when it confronts real players.

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