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Optimization, Learning Algorithms and Applications

Second International Conference, OL2A 2022
Póvoa de Varzim, Portugal, October 24–25, 2022
Proceedings

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Editors
Ana I. Pereira
Instituto Politécnico de Bragança
Bragança, Portugal

Andrej Košir
University of Ljubljana
Ljubljana, Slovenia

Florbela P. Fernandes
Instituto Politécnico de Bragança
Bragança, Portugal

Maria F. Pacheco
Instituto Politécnico de Bragança
Bragança, Portugal

João P. Teixeira
Instituto Politécnico de Bragança
Bragança, Portugal

Rui P. Lopes
Instituto Politécnico de Bragança
Bragança, Portugal

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Preface

This CCIS volume 1754 contains the refereed proceedings of the Second International Conference on Optimization, Learning Algorithms and Applications (OL2A 2022), a hybrid event held during October 24–25, 2022.

OL2A 2022 provided a space for the research community on optimization and learning to get together and share the latest developments, trends, and techniques, as well as to develop new paths and collaborations. The conference had more than three hundred participants in an online and face-to-face environment throughout two days, discussing topics associated with optimization and learning, such as state-of-the-art applications related to multi-objective optimization, optimization for machine learning, robotics, health informatics, data analysis, optimization and learning under uncertainty, and Industry 4.0.

Five special sessions were organized under the following topics: Trends in Engineering Education, Optimization in Control Systems Design, Measurements with the Internet of Things, Advances and Optimization in Cyber-Physical Systems, and Computer Vision Based on Learning Algorithms. The OL2A 2022 program included presentations of 56 accepted papers. All papers were carefully reviewed and selected from 145 submissions in an single-blind process. All the reviews were carefully carried out by a scientific committee of 102 qualified researchers from 21 countries, with each submission receiving at least 3 reviews.

We would like to thank everyone who helped to make OL2A 2022 a success and hope that you enjoy reading this volume.

October 2022

Ana I. Pereira
Andrej Košir
Florbela P. Fernandes
Maria F. Pacheco
João P. Teixeira
Rui P. Lopes

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Contents

A Review of Dynamic Difficulty Adjustment Methods for Serious Games

Júlio Castro Lopes[1] and Rui Pedro Lopes[1,2(✉)]

[1] Research Center in Digitalization and Intelligent Robotics (CeDRI), Instituto Politécnico de Bragança, Bragança, Portugal
{juliolopes,rlopes}@ipb.pt
[2] Institute of Electronics and Informatics Engineering of Aveiro (IEETA), University of Aveiro, Aveiro, Portugal

Abstract. Rehabilitation games can be a novel and effective approach to mental and physical rehabilitation. Since patient's abilities differ, these types of games depend on a variety of levels of difficulty. Furthermore, it is prudent to make continuous adjustments to the difficulty in order to prevent overburdening the patient, whether on emotional or physical level. For this purpose Dynamic Difficulty Adjustment (DDA) can be a very interesting solution, as it allows for the dynamic adaptation of the game based on observed performance and on physiological data of the player. DDA has been used in games for many years as it allows tuning the game to match the player's ideal flow, keeping high levels of motivation and challenge. This paper reviews several DDA approaches used in rehabilitation and entertainment games. We concluded that many studies use Reinforcement Learning (RL) because it requires no pre-training and can adapt the game in real time without prior knowledge.

Keywords: Dynamic difficulty adjustment · Serious games · Rehabilitation · Reinforcement learning

1 Introduction

Games, whether in video or Virtual Reality (VR) format, are usually accomplished through a series of levels of increasing difficulty. When playing games either offline or online, the intuitive approach is to divide them into three difficulty levels [22], commonly labeled as: easy, medium, and hard [32]. This division in three levels can be seen in several applications, such as educational games [27], virtual reality games [9], video games for entertainment purposes [36], and even on gamification systems for educational purposes [18]. Although this division into three levels can be seen as the standard approach, in some cases it can be extended to accommodate more levels or finer degrees of difficulty. The authors in [24] concluded that their game should have more than three levels of difficulty because the player would frequently get stuck on either the lower or higher difficulty.

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Many games allow the user to select the desired level of difficulty at the beginning of the game, that will be kept until the player decides to change it. When the user is playing a game for the first time, deciding on his/her own can be difficult because they have no idea about the difficulty of each level and do not know the relative level of their skills [22]. Furthermore, requiring players to select difficulty levels on a regular basis may be inconvenient and cause game interruptions. A different approach could be followed through Dynamic Difficulty Adjustment (DDA).

The objective of the work described in this paper is to assess, in the scientific literature, the techniques and algorithms used in video-games to adapt the environment to the player's skills and stress level. It is an ongoing work, within the GreenHealth project [19]. This project, focusing on mental health rehabilitation in people diagnosed on the schizophrenia spectrum, has the main goal of developing and using digital technologies, such as Facial Expressions classification under occlusion by Virtual Reality (VR) goggles [28], Game-Based Learning (GBL), Internet of Things (IoT), Artificial Intelligence (AI), and Advanced Data Analytics (ADA), in the development of innovative rehabilitation techniques, contributing to the promotion of well-being and health in a holistic perspective. The approaches to be developed depend on an adequate and motivating simulation in virtual reality, to increase the impact and success of the rehabilitation procedures.

This paper is structured in four sections, as follows: Sect. 2 describes the methodology used to perform this review, Sect. 3 and Sect. 4 focus on a literature review on game DDA, approaching entertaining games and rehabilitation games respectively; Sect. 5 presents an analysis of the described games in the format of a table; and conclusions are drawn on Sect. 6.

2 Methodology

As mentioned before, the main objective of this literature review is to try to understand the techniques and algorithms for the dynamic adaptation of games in a cognitive rehabilitation scenario. This literature review follows the approach suggested by Materla et al. [20] and by Subhash and Cudney [35]. It is composed of three phases, starting with the planning, followed by the operation (conducting) and dissemination (reporting) phases. The planning phase included both the definition of the bibliography databases and the selection of the query term. The selected databases were Scopus and Web of Knowledge (WoK), since they provide the most relevant and accurate results. The query used the term ("(game OR gaming OR games) AND (adapt OR adapted OR adapts OR adaptation OR readaptation OR adapting) AND (dynamic difficulty adaptation OR dynamic difficulty balancing OR DDA OR dynamic)") for the title, keywords and abstract. The papers were further restricted to the last 13 years, from January 1st, 2009 and December 31st, 2021. Only papers available in the institutional repositories, peer reviewed and written in English were considered. The second phase (conducting) started with the selection of the relevant papers and exclusion of the remaining. Repeated papers and papers without available full-text

PDF were excluded. After these step, a total of 379 papers remained. The process continued with the selection of the most relevant articles, through title and abstract analysis. Non relevant papers were eliminated. Subsequently, the most relevant papers remained, in a total of 12 (Table 1). Note that we have used a wide range of years (from 2009 to 2021), since [17] work, is a well-known and one of the first approaches to solve DDA problems.

3 Dynamic Difficulty Adjustment

When people engage in an activity that is neither boring nor frustrating, they become engrossed in it, allowing them to work for longer periods of time and remain focused on the task. The flow channel is a state of mind whose ideas can be applied to a video game [8]. Following the flow, the idea of using adaptive difficulty mechanisms, is to keep the game's difficulty within a certain range to prevent the player from getting bored if the game is too easy, or frustrated if the game is too difficult. In recent years, there has been a lot of research done on DDA applied to games [39].

DDA aims to adapt the difficulty of the game based on the players' performance, and can be accomplished by considering not only their in-game performance, but also the associated physiological responses. By measuring and integrating physiological data it is possible to map how difficult or easy it is for the player to perform a given task [17]. The study in [34] demonstrated that DDA based on electroencephalography (EEG) signals improved the players' game experience. This statement was backed up by their opinions.

Huber et al. [12] demonstrated the use of experience-driven Procedural Content Generation for DDA in VR exercise games by procedurally generating levels that match the player's current capabilities. Deep Reinforcement Learning (DRL) algorithms were used to adjust the structure of the maze and decide which exercise rooms to include in the maze, in order to match with the player's capabilities. Since most established DRL algorithms share the fact that the required amount of training effort increases with high-dimensional input state spaces, they did not train the algorithm to create mazes from scratch. Instead, they adopted a procedural technique similar to [13]. Because human players require a minimum amount of time to complete each maze, the authors decided not to train the network solely with training data generated by real human players. As a result, they decided to train their network on a user simulation of the difficulty of a given maze. Since the DRL algorithm's goal is to create a maze with the desired difficulty level, the reward is based on the player's difficulty rating (via questionnaire) at the end of each maze. They also took an electrocardiogram (ECG) signal to objectively measure the participants' exertion level during the VR session. They confidently stated that, in addition to traditional in-game parameter adjustment, procedural generation of levels with appropriate difficulty can improve future DDA systems for exergames. However, they also found two drawbacks in their approach: the generated levels took too long to allow for fast adaptation, and the usage of a static user simulation.

Tan et al. [37] proposed two adaptive algorithms that leverage principles of Reinforcement Learning (RL) and evolutionary computing to increase player satisfaction by scaling the game AI difficulty while the game is being played. The proposed algorithms, Adaptive Uni-Chromosome (AUC) and Adaptive Duo-chromosome Controller (ADC), have the advantage of not requiring a training phase, as adaptation occurs during the game session. The controller's behavior-based system can be seen as advantageous due to its scalability, which means that new behavior components, whether complementary or antagonistic, can be easily added or removed from the existing set of behavior components. The adaptive algorithm will automatically select a behavior component combination that is appropriate for its opponent. The AUC controller has the particularity that it can be trained online, which means that the training and adaptation can take place in real time while playing the game. The authors also investigated the effects of varying the learning rate and mutation rate for both algorithms, and they proposed a general rule of thumb for selecting these two parameters. They came to the conclusion that the adaptive controller is only as good as its design, and that it is unable to adapt to a player who exceeds its full potential. As a result, a learning and adaptive game AI would be a natural future extension.

Liu et al. [17], developed an affect-based DDA system for computer games. The game difficulty level is automatically modified in real time as a function of the player's affective state, using physiological data to determine his or her probable anxiety level, which was chosen as the target affective state. The gaming experiences of the participants were reviewed and contrasted when a performance-based DDA mechanism and an affect-based DDA mechanism were used to the same computer game. To the best of the authors' knowledge, this was the first time that the effects of an affect-based DDA on player interaction with a computer game capable of physiology-based affect recognition and real-time difficulty adjustment in a closed-loop way have been explored experimentally. The affect-based DDA improved the overall satisfaction of gaming for the majority of participants, with 77% reporting more challenging gaming experiences. These findings imply that a computer game's ability to recognize a player's affective states and alter game difficulty correspondingly, could improve the gaming experience. Although the affective modeling methodology used in this study could be used to detect the intensity of anxiety, excitement, and frustration at the same time, more sophisticated difficulty adaptation mechanisms would be required to incorporate multiple inferred affective cues and account for other game-playing information of interest, such as the player's performance, personality, and the context and complexity of the game [17]. The authors conducted a preliminary session consisting of six one-hour gaming sessions in order to train their Regression Tree (RT), which was the model used in this work based on their previous research [26]. One of the paper limitations, according to the authors, is the use of physiological sensors by the players, which may be uncomfortable to wear. They emphasized that, as technology advances, these sensors may improved to the point of being imperceptible during the gameplay. Another disadvantage and possibility for future improvement, is to incorporate a method based on RL to perform the adaptation in real time without a previous training process, leading to real time adaptation. This would allow eliminating the need to perform preliminary gaming sessions, to collect training data. The authors' recommendation, on the other hand, was to implement Active Learning (AL). AL and RL are related in that both can reduce the number of labels required for models. Nonetheless, by using AL, you still need to collect data to train the model (although, fewer than the authors' proposal), which should reduce the training time.

Chanel and Lopes [6] built a Tetris game that changes its complexity dynamically, based on an emotional model capable of recognizing anxiety and boredom from raw human physiological data (extracted by electrodermal activity signals). This paper begins by comparing a Linear Discriminant Analysis (LDA) and a Quadratic Discriminant Analysis (QDA), with the combination of Deep Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM). The authors achieved slightly better accuracy and managed to train models capable of identifying the most useful features of the signals and better representation of the problem through intermediary layers. Two types of adaptation methods were investigated: one that uses the model decision directly - absolute (ABS), and the other that compares the previous model output with the current one and then adjusts the difficulty accordingly - relative (REA). The ABS method outperformed the REA method, according to the results. When players stated that they wanted to play on hard or medium difficulty, the ABS model was especially effective at adapting the game difficulty. Based on their previous study [7], the authors only considered two possible emotional states: boredom and anxiety. This can be seen as a disadvantage in studies that require more detailed expressions and emotional states to be analyzed. In order to train the model, the authors collected physiological activity from 20 participants over 6 sessions of 5 min each (10 h of data) while playing Tetris. The authors also mentioned that their adaptation methods only have two outcomes, in direct connection with the emotional states: increase or decrease difficulty. However, a potential third class (maintain difficulty) may be advantageous for ambiguous values outputted by the model. Future enhancements to the proposed models may be obtained if, in addition to physiological data, information from the gameplay was used as input.

Blom et al. [2] published a DDA system based on Facial Expression Analysis (FEA) for predicting in-game difficulty and acting as a modeling mechanism for single player arcade games. Their system performs online adaptation and has the particularity that it is unobtrusive, which means that the user will not feel any discomfort while acquiring facial expression information. They choose to focus on personalising the game space to the individual player with respect to experienced challenge (adapting the game environment, instead of adapting the behaviour of the game characters). This study was divided in two main parts. The first part looks into the connection between in-game difficulty and the emotional condition of the players as expressed through their facial expressions. This was accomplished through the use of classification methods, that allowed the authors to predict the difficulty level of the game being played with good accuracy, by analyzing players' facial features. Based on first part's findings, the second part expands it and introduces FEA as a technique for evaluating player involvement and dynamically changing in-game difficulty. Since player facial expressions are an indicator of current game difficulty, they proposed a FEA-based game personalisation system that aims to improve individual player in-game experience while also maximising player affection levels towards the game itself. To train their model, participants were asked to rate the difficulty of the game on a scale of 1 (very easy) to 7 (very difficult). This value was considered as "perceived difficulty". These values were used in a classification task in which the goal was to predict the difficulty level of the game. The trained model consistently correlated different facial expressions (including head movement) to a specific user challenge level, resulting in smoother in-game adaptations, whereas the same user behavior would result in steep adaptations in the heuristic system. As a result, they concluded that online and unobtrusive game personalisation is possible using only facial expression analysis, and that head pose detection can contribute to an even more effective game adaptation mechanism. They also detected a preference for the personalized system in 18 of 30 tests, while the static system was preferred in only 9 of 30 tests. To improve their work, the authors proposed enriching the training set with observations from more players, regardless of age, gender, or skill level, as well as incorporating more features into their classifier to improve player modeling.

4 DDA on Rehabilitation Games

Game-based rehabilitation can be an effective way to engage patients in therapy and, at the same time, develop innovative rehabilitation challenges. Games can provide a fun and entertaining way to perform rehabilitation, but the real focus is on performing a set of exercises that will aid in patients' rehabilitation process. An adaptive therapeutic game can be very beneficial, since it can change the game behavior based on the patient's results. It can thus adjust the game difficulty dynamically based on the patient's capabilities assessment and motivation, rather than a static user profile. As a result, adaptation can bridge the gap between the patient's health status during the game and the assumed patient profile at the start of the therapy session paradigms [14].

Earlier in 2011, Hocine et al. [11] produced a pre-pilot experiment for a therapeutic serious game, but with abstract information about the DDA technique, intended to reuse it in different games. The proposed technique includes a generic real-time adaptation module that allows each patient's game difficulty to be dynamically adjusted based on his profile and observed performance. To accomplish this, the authors devised a structure known as a matrix of action probabilities, which represents the game's 2D plan. This matrix was constructed by taking into account the presence of a challenge in the game, which required the collection of information about the patient. This stage is known as the assessment, and it results in a matrix with each position $A(i, j)$ representing the patient's success rate. In this, each location $D(i, j)$ holds a probability that an action should be performed at this location by the patient. With this knowledge, the game level must direct game actions toward the locations with the best chances of success. This structure is advantageous because it provides a common interface for all games. This means that the difficulty adaptation module is treated as a black box by the game level, producing a matrix of action probabilities. The DDA module can bridge the gap between the patient's current health status and the profile assumed at the start of the therapy session. Their abstract DDA module was later integrated in Hocine et al. serious game for motor rehabilitation in 2014 [10]. This online adaptation was accomplished by making the following decisions: (i) reduce the difficulty to avoid putting the player in repeated failure situations during the game level; (ii) increase the difficulty when the player has a string of consecutive successes and finds the game to be very easy; and otherwise (iii) maintain momentarily the difficulty [10]. In comparison to the control strategies, DDA increased the number of tasks, number of successful tasks, and total distance. This is a critical factor that allows stroke patients to increase their training volume. The authors also concluded that in future work, the number of subjects and different profiles should be increased.

RL algorithms can be a good approach for dynamically adapting the game while taking patient performance into account at run time. Ávila et al. [29] presented a novel game difficulty adaptation algorithm that efficiently balances the adaptation by conjugating information from the patient's game performance and therapist feedback. A Markov decision process (MDP) was used to define an initial adaptation policy, that was then fed to an RL algorithm, which dynamically updates the adaptation policy by incorporating action rewards (whether negative or positive) from the therapist. The authors have chosen a RL approach because actions are also based on the current state of the system but, unlike the MDP, the decision policy is dynamic and evolves based on given rewards. By monitoring the patient execution, the adaptation policy determines whether to increase or decrease the game level difficulty. The authors have created a modified version of the latter (Q-l+) that computes the action value function by incorporating both the rewards derived from online monitoring of the patient's performance and the rewards set by the therapist as therapy progresses, which they call reward shaping [15]. Because RL policy evolution requires long training periods with initial behavior that is close to erratic, the RL algorithm was seeded with the static policy discovered with the MDP in this game adaptation approach [25]. The learning process is accelerated in this way, and a dynamic optimal policy is always available [29]. This study was limited by therapist guidance because it requires on-line therapist feedback; as an improvement, this system could be updated to an automatic system that does not require any mandatory assistance.

Andrade et al. [1] provided an RL approach to dynamically modeling player capabilities in applications that combine gaming and rehabilitative robotics.

Robots and serious games can be useful rehabilitation tools because they can integrate multiple repetitive movements with only prior programming. In order to adapt the difficulty of the game to player's skill level, the authors have modified the Q-Learning algorithm, with SARSA [33]. The authors made it clear that variables that have a direct effect on game difficulty were chosen to serve as environment states. They used the inverse of the Euclidean distance from the current state to the final state to calculate the immediate reward given at each step interaction (Eq. 1). The reward indicates how far the player has progressed away from the most difficult game level.

$$r = \frac{1}{\sqrt{(v_m - v_i)^2 + (d_n - d_j)^2}} \tag{1}$$

In order to assess the user's performance, the authors take into account not only game scores but also the number of challenges (exercises) the user performs, as measured by its actual movement. It is worth noting that the algorithm chooses the start state at random, so the game could begin at either an easy or challenging level. This study only includes thirty-minute experiments with four players, but the results show that the proposed approach is feasible for modeling user behavior and capturing adaptations and trends for each player based on game difficulty. The authors intend to extend this to clinical subjects in the future, using the obtained map as a guideline for how to make the game easier or harder for each individual player.

Sekhavat et al. [30], presented a customized DDA approach for a rehabilitation game to improve functional arm capabilities, that automatically changes difficulty settings in real-time based on a patient's skills. Since existing RL algorithms are episodic (all objectives are evaluated in the same predefined episodes), the authors decided to modify this idea in order to evaluate a problems' objectives at different times. They needed to find a different approach because DDA requires the history of previous evaluations to evaluate some objectives rather than just the evaluation based on the information at the end of each episode. This opened the need for a Multiple-Periodic Reinforcement Learning (MPRL), which allows for the evaluation of value functions of different goals in separate periods. In the MPRL architecture, the authors stated that some goals may be evaluated more frequently than others. Goals that are evaluated frequently necessitate a shorter history of outcomes, whereas goals that are evaluated infrequently necessitate a longer history of outcomes [30]. When there are direct relationships between goals, it is possible to extract a single objective function by considering the goals all at once. In the case of completely unrelated objectives, on the other hand, reward functions and decision-making policies can be considered separately. The authors used an AUC Controller [37] to demonstrate how game parameters (such as speed, size, and distance) can be changed to meet the objectives. The main advantage of this controller is its ability to train and adapt in real-time while playing the game. The game properties are represented by six real numbers stored in this AUC controller. The controller chromosome simulates the game's difficulty by encoding a set of behaviors that is expected to be difficult enough to earn a score. The chromosome is randomly initialized at the start of the game. They proposed new semantics and procedures for MPRL with two-level probabilistic actions. One of the goals of this study, was also to compare the traditional Multiple-Objective Reinforcement Learning (MORL) with their MPRL. The different between this two definitions of RL is the following: MORL is a significant version of RL that considers many goals for decision-making (all the goals evaluated at the same time), and MPRL is distinguished by its capacity to analyze distinct objectives at different times. They proved that MPRL outperforms traditional MORL in terms of player satisfaction indicators as well as improving the motor control system over time, according to the results of a series of experiments on patients. Their system is limited because it only considers player skill level; learning about his/her play style and individual characteristics would be beneficial. Because MPRL must handle multiple objectives at the same time, the authors did not achieve a high level of accuracy.

Although all of the rehabilitation studies mentioned thus far only take players' performance or their emotional state into account, it can be an effective approach to combine both while playing the game. Pezzera et al. [23] implemented a preliminary version of their home rehabilitation platform on healthy subjects, with the intention of later testing it on patients with multiple sclerosis. Commercial exercise games are not a suitable match for rehabilitation: they may be too risky or difficult to play with, as they typically only offer a few fixed degrees of difficulty, designed for those who are not disabled. For people who have trouble executing specific movements, this may be insufficient. Furthermore, the therapist rarely has access to the raw data collected by the tracking devices, making it impossible to make a quantitative assessment of the patient's performance. Because of these factors, the authors decided to implement DDA in the game, through three independent modules that collaborated to conduct the DDA:

1. an off-line adapter, which computes the patient's ability using data from previous exercises, used as a starting point for determining the appropriate difficulty level;
2. an emotional adapter, based on the outcome of conversations between the patient and an Empathic Virtual Therapist (EVT) [38], where the EVT produces an assessment of the patient's emotional status;
3. an on-line adapter, that adjusts the difficulty level based on the player's score and motion accuracy.

These modules can be used together or separately, but the best results were obtained when combined. To assess the performance of the player, the authors have used the Eq. 2.

$$pi = \alpha FPA(R_h, R_m) + (1 - \alpha) FMA(G_h, G_m) \tag{2}$$

where:

FPA - Fully Performance Adapter: it only uses the hit rate information and ignores the monitor's value.

FMA	- Fully Monitoring Adapter: from a rehabilitation standpoint, it is safer because it only uses monitor information to adjust the difficulty; even if the patient has a perfect hit rate, the difficulty will not be increased unless the monitors have a good value.
R_h	- repetition hit rate.
R_m	- repetition monitors activation rate.
G_h	- global hit rate.
G_m	- global monitors activation rate.
$0 \leqslant \alpha \leqslant 1$	- the therapists will set this parameter based on the patient's recovery.

The authors have implemented two possible algorithms for the FPA and FMA, namely a linear adapter and a fuzzy adapter. When the hit or miss rate exceeds a certain threshold, the linear adapter simply adjusts the difficulty by increasing or decreasing the parameters by a fixed amount. The fuzzy adapter, on the other hand, maps inputs to a fuzzy set and uses fuzzy inference to determine the new level of difficulty. However, patients who do not want to talk with the EVT may choose to ignore the virtual agent because their moods can change throughout the day and not every single player has the patience to answer the virtual agent at each evaluation. Instead of using a virtual agent, this system can be improved by incorporating an automatic mechanism (perhaps based on the emotional state of the players). The authors concluded that incorporating an RGB-D camera to track the patient's body during the game and also to determine the patient's emotional state would be a prudent solution.

Balan et al. [4] presented a VR game for treating acrophobia, based on the concept of real-time automatic adaption of in-game height exposure dependent on the subject's level of fear. To that purpose, they employed physiological signals as input (EEG, Galvanic Skin Response - GSR, and Heart Rate - HR) to forecast the future exposure scenario and estimate the subject's current fear level. The authors have created three modes of expressing fear ratings: the 2-choice scale, the 4-choice scale, and the 11-choice scale. Three fear-level scales were used, with 2, 4, and 11 possible responses (2-choice, 4-choice and 11-choice scale). They used a variety of ML classifiers and DL techniques to determine the current anxiety level and the next exposure scenario, including Support Vector Machine (SVM), k-Nearest Neighbors (kNN), LDA, RF, and four deep neural network architectural models. Two classifiers were used: one to estimate the patient's current fear level (C1) and one to identify the appropriate treatment based on the target fear level (C2). A early experiment in which eight acrophobic individuals were *in vivo* and virtually exposed to various heights yielded the data necessary to train the classifiers. Both a user-dependent and a user-independent modality were employed to calculate the classifiers' accuracy. In the case of the user-independent modality, each classifier was trained using the data of the other individuals. In their experiment the authors concluded that cross-validation scores were a good choice, achieving very high scores for both classifiers, highlighting the kNN and RF techniques. Concerning the physiological signals used as input for the classifiers, the authors concluded that GSR, HR, and EEG values in the beta range were the most important features for fear level classification. The authors hope to develop a VR-based game for treating additional sorts of phobias in the future. Furthermore, they plan to expand the trials and include more people, with their physiological reactions being collected and utilized to train and test the classifiers. Another path they will take is to conduct real-world testing with the 8 acrophobic patients who took part in the current study, exposing them to *in vivo* circumstances and assessing whether their anxiety levels decreased.

Later, the authors expanded their research to include physiological signals as well as patient facial expressions and respiration rate [5]. In this pilot experiment, they proposed a model for automatically adapting exposure scenarios based on the emotional states of the users, which was tested on four acrophobic subjects. This system employs an intelligent virtual therapist who can recognize emotions based on physiological signals, offer encouragement, and adjust exposure levels based on the user's moods.

5 Discussion

This section provides a brief description and comparison of the described papers, in order to draw conclusions about the games described in this paper (Table 1).

It is possible to see that there are studies that only consider the performance of the player, others its emotional state and just few that integrate both into their DDA module. Although the majority of these authors concluded that incorporating players' performance and emotional state rather than just one of them, could be a solution to improve the game.

The studies described before show that it is possible to dynamically change the difficulty of the game using a variety of sensors/data sources. Some of the studies use things as simple as the keyboard, computer, mouse or even a graphics tablet. The majority of these studies only consider the player's performance within the game because it is the only thing they can extract from this type of data source. More complex studies use sensors and cameras, not only to extract the performance of the player in game but also to extract his/her emotional state. Some of the sensors may be considered a limitation since they can be intrusive and uncomfortable to the player. Despite this, as technology advances, sensors become more discrete and efficient [16].

Although there are some existing reviews on DDA systems and methodologies [3,21,31,39], our review is unique in comparison to all of them, making it important to the scientific community. The Table 2, provides a brief overview of

Table 1. Overview of dynamic difficulty adjustment games

Study	Game type	Sensors/Data source	Techniques used	Achievements	Limitations
Huber et al. [12]	Virtual Reality Entertainment Game	Head-Mounted Display (HMD); Electrocardiogram (ECG) sensor attached to patient's upper body	Deep Reinforcement Learning	Generation of levels based on player's skills.	Static user simulation. Generated levels to slow to allow for fast adaptation.
Tan et al. [37]	Entertainment Computer Game	Keyboard; AI algorithm	Reinforcement Learning; Adaptive Uni-Chromosome; Duo-chromosome Controller	Training is not required; adaptation takes place during the game session.	The adaptative controller is only good as its design; unable to adapt if a player exceeds its full potential.
Liu et al. [17]	Entertainment Computer Game	Wearable biofeedback sensors	Machine Learning Classifiers Highlited: Regression Tree	Dynamic difficulty adjustment based on players' affective state.	Unconfortable sensors. Training time too long.
Chanel et al. [6]	Entertainment Computer Game	Electrodermal Activity (EDA) sensors	Deep Learning Techniques	Dynamic adaptation of the game, based on two possible emotional states.	Module just uses physiological data, nothing related to player's performance.
Blom et al. [2]	Entertainment Computer Game	Computer Camera	Machine Learning Classifiers; Heuristic Algorithm	Dynamic difficulty adjustment based on players' facial expression.	Adaptation based only on players' facial expression. More features could be added.
Hocine et al. [10]	Motor Rehabilitation	Computer Mouse; Graphics tablet	Monte Carlo Tree Search; Reward Based System; Computer Vision Algorithms	The game adapts to each profile in real time.	The number of different subjects and profiles is limited.
Sekhavat [30]	Motor Rehabilitation	Microsoft Kinect	Reinforcement Learning (RL); Multiple-Periodic RL	Automatic Adaptation based on real time patient's skills.	Low accuracy. It only considers players' skill level.
Ávila et al. [29]	Motor Rehabilitation - Virtual Reality Based	Abstract definition of the method; it was unclear how data was received	Reinforcement Learning; Markov Decision Process	Online Adaptation during game.	The therapist needs to be available during game.
Andrade et al. [1]	Motor Rehabilitation	Robotic Device	Reinforcement Learning	Motor Rehabilitation using robotics.	Small sample size. Just four players were included.
Pezzera et al. [23]	Motor Rehabilitation	Microsoft Kinect; Nintendo Wii Balance Board	Fuzzy Logic	Adaptation based not only on players' performance but also on theirs' physiological state.	Physiological state extracted by Virtual Theraphist during game, could be improved with other mechanisms, such as cameras, sensors, etc.
Balan et al. [4]	Mental Rehabilitation - Virtual Reality Based	Acticap Xpress Bundle (EEG data); Shimmers Multi-Sensory (HR and GSR data)	Machine Learning classifiers; Deep Neural Networks	Virtual reality game that dinamically adapts its' difficulty based on patient current level of fear.	Small sample size, possibly leads to overfitting.
Balan et al. [5]	Mental Rehabilitation - Virtual Reality Based	Two HTC Vive Trackers; HMDS; EEG Device	Machine Learning classifiers; Deep Neural Networks	Adaptation based on physiological signals, facial expression and respiration rate.	Small sample size. Discomfort in the head by using sensors.

recent reviews in DDA, proving that our review can fill a gap in the literature by reviewing several DDA rehabilitation games.

The majority of existing DDA studies make use of RL techniques or ideas derived from them (reward based systems). RL algorithms have high expression in the studies, because they do not require pre-training, which means they do not require any prior knowledge to adapt to the abilities of players. The review performed in this paper will serve as a basis for future work within the Green-Health project [19], aiming at filling the gap in the literature on games for mental rehabilitation, with a particular emphasis on patients with schizophrenia.

Table 2. Recent review papers in DDA

Study	Summary
Panagiotis et al. [21]	This is a very complete and recent review. This can be seen as the most similar review to our, however, our paper details several different studies, mainly the ones that focus on rehabilitation purposes.
Sepulveda et al. [31]	Provides an overview of the development of a DDA system in video games. However, instead of detailing concrete DDA approaches, it focuses on the global implementation of a DDA system.
Bontchev et al. [3]	Deals with models for presenting emotions, techniques for measuring behavioral signals, emotion recognition and adaptation mechanisms using affective feedback. It focuses on entertainment games rather than rehabilitation games.
Zohaib et al. [39]	Describes several different methods for performing DDA in games, with an emphasis on providing an overview of various types of methods. This is a more general review that focuses on the classification of DDA approaches.

6 Conclusions

This paper provides an overview of DDA applications in games, with a focus on rehabilitation games. Throughout this review, several techniques to perform DDA, such as fuzzy logic, heuristics, ML, and DL techniques and also RL (the most popular in our review) were described. This was not an extensive review; rather, this paper reviews the studies that have the application context most adequate to cognitive and social rehabilitation of patients, the focus of the project this work is being developed.

It is evident, from the study performed, that a useful rehabilitation game, based on virtual reality simulation, can benefit from a Reinforcement Learning DDA system that use several inputs as basis for decision. It should include the in-game performance, the emotional state (measured through facial expressions, head pose, body pose, physiological data) and even human input, to make adjustments during rehabilitation sessions.

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