Dynamic Difficulty Adjustment of Serious-Game Based on Synthetic Fog using Activity Theory Model

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***Abstract*—This study used the activity theory model to determine the dynamic difficulty adjustment of serious-game based on synthetic fog. The difference in difficulty levels was generated in a 3-dimensional game environment with changes determined by applying varying fog thickness. The activity theory model in serious-games aims to facilitate development analysis in terms of learning content, the equipment used, and the resulting in-game action. The difficulty levels vary according to the player's ability because the game is expected to reduce boredom and frustration. Furthermore, this study simulated scenarios of various conditions, scores, time remaining, and the lives of synthetic players. The experimental results showed that the system can change the game environment with different fog thicknesses according to synthetic player parameters.**

***Keywords*—Dynamic difficulty adjustment; serious-game; activity theory model; synthetic fog; synthetic player**

I. Introduction

One of the most significant challenges in successful teaching is preparing a suitable learning environment [1]. Several studies have shown that appropriate teaching methods are usually active, engaging, goal-oriented, [2] generate spontaneous random feedback, and provide solutions to challenges [2], [3]. The last two characteristics are also possessed through instructional content when playing games embedded in a computer [4]. Scientifically, this category of game is called a serious game [5], and it aids in making the learning process more interesting, fun, comfortable, effective, improves learning performance, student's skills, and behavior [5], [6].

This research aims to change the habits, ways of thinking, views, increase knowledge, and train the soft skills of serious-game players. It also increases engagement, extrinsic and intrinsic motivation, creates awareness, and analyzes games developed to focus on a particular lesson, which can be played in the classroom or at home.

Carvalho et al. [7], [8] proposed a scheme to analyze and evaluate various student experiences with learning material for later aggregation and study. According to Callaghan et al. [9], the serious-game view is complex and covers three principal activities, namely gaming, learning, and instructional, comprising the student and the teacher. The game consists of basic supplementary attempts or resources obtained from the teacher.

The Activity Theory Model Serious-Game [10] (ATMSG) method [8] comprises four analytical phases. In the first stage, the teacher explains the critical tasks relevant to the system action and defines the course and theme. The second stage establishes a sequence as a map to help define the game's core elements and provide an initial point for determining the interlinked aspects of the system framework. In the third stage, the trainer describes elements relevant to each node of the game [11] order. While in the last phase, the teacher collects suitable acts, resources, and targets that equally belong to the game order. After completing the phase, the trainer has a summary of the play structure, knowledge, and didactic components, as well as their application.

However, some weaknesses are associated with the serious game, such as difficulty in playing, which sometimes frustrates the players. To overcome these weaknesses, the player must achieve a state of "flow" [12][13], which is usually characterized by sustained concentration and increased achievement. Several studies proposed Dynamic Difficulty Adjustment (DDA) [14]–[19], a mechanism to dynamically maintain a game's difficulty level [20]–[22] to ensure an increase in user's interest.

The mechanism of dynamic difficulty adjustment starts with processing data from players and enemies in the game and changing the difficulty level [23]–[26] based on the player's skill. The attributes of both parties are usually changed to dynamic, and the more skilled the player, the greater the possibility of the system limiting resources and the harder it will be to beat the enemies. However, when the player suffers defeat, the game will provide weaker enemies and abundant resources [27].

Several studies have examined DDA in games, such as computer-controlled players [27], and inferred difficulty curves from real-time data [28]. These studies developed automatic difficulty selection [29], applied appropriate difficulty based on player information [30], determined the effect of difficulty setting on trust players [31], and produced dynamic game content based on evidence-centred design [32]. However, this study will adopt simpler and faster techniques [32] by using a dynamic value to adjust the game's difficulty level.

This study proposes the automatic DDA based on synthetic fog setting to reduce players' visibility. Artificial fog technique is widely used to measure fog removal techniques from natural images [33]–[36]. Nevertheless, artificial fog is more used to produce difficulty when playing games, adding a mysterious experience and increasing tension. This technique has not been previously used in preliminary studies to determine difficulty level because artificial fog is an art without any standards. Moreover, the in-game synthetic fog only serves as a compliment.

A synthetic agent [37][38]–[41] was used to determine the serious-game [42] dynamic difficulty levels that should be achieved based on the final target scenarios, which is modified at each level.

II. Related Works

A study conducted in 2015 [43] proposed setting the difficulty of the enemy character, which can change their nature and behaviour, based on the game player's ability. It only focused on changes in the conduct of the enemy's character with the difficulty setting method completed [44] using an evolutionary algorithm. Lach [45] used an adaptive evolutionary algorithm to regulate non-player characters' behaviour. These approaches do not provide details of the framework used for the serious-game foundation.

Callaghan proposed using a serious-game framework based on activity models [8] to integrate analytical techniques in engineering lessons in 2018 [9]. However, the approach taken does not consider adaptive difficulty management.

Another research article [30] proposed using a fuzzy coordinator for dynamic difficulty setting in commercial games applied to bots. Although the study described the behaviour of smart bots, which have a variety of capabilities, it was not applied in serious games.

A dynamic process was used by [29] to determine the difficulty setting in video games without stating the use of methods and parameters set dynamically at each level. The report by [28] also proposed a dynamic difficulty setting, for puzzle games, using a rating system. Preliminary studies [28], [29] have not implemented the serious-game strategy because they do not use machine learning methods.

A previous study by [32] proposed a dynamic difficulty setting in game-based learning using the ECD framework to design and assign each student's competency. A dynamic difficulty setting was designed by changing the non-player character's attributes that can balance the abilities of students who are playing dynamically. The study focused on educational content questions without considering the game environment setting. It also introduced the ECD framework for dynamic difficulty management [32], focusing on mathematics using standard Indonesian student exams. These studies focused on the evidence used as a reference to process dynamics more accurately and effectively.

The study by [27] proposes creating an enemy using the dynamic difficulty setting and applying it to the business content. The dynamic difficulty setting handles two strategies, namely enemies who can decide strategies and provide threats to players, who are expected to be more involved in the game.

An architecture was proposed in [46] to produce enemy formations in a procedurally two-dimensional game. This was carried out to determine the variable difficulty curve and enemy variation used to design an appropriate difficulty setting based on the fitness function calculation [47]. The study by [46] presented the dynamic difficulty adjustment with a skill chain and ranking system used to balance the game's difficulty. Their discussion suggested that the skill chain can be useful for getting players to complete a higher number of tasks with a greater difficulty level.

Studies on the dynamic difficulty setting of the serious game are challenging to explore. To date, no system has been proposed, using the concept of the activity theory model [9], irrespective of its numerous advantages and convenience in developing and analyzing the learning strategies of the games.

Meanwhile, the serious-game dynamic difficulty setting system with the activity theory model has a more detailed division and is more suitable for an educational game. Several studies have discussed the dynamic difficulty settings [27][48][47] aimed at enemy characters capable of deciding strategic behaviour and producing appropriate attack formations. It also uses skill chains to produce balance by providing several missions with a higher level of difficulty. However, this present study aims to design a dynamic difficulty management system which uses the activity theory model to determine environmental changes and the difficulty level of the serious game. This process is carried out by applying synthetic agents as substitutes for players to facilitate analysis. The contributions of this research are described in the following paragraphs.

First, a dynamic difficulty adjustment is proposed in the activity theory model of the serious-game. The system reads the player's parameters' initial value and then re-reads it after the player receives an award. Based on reading this second parameter, the system can dynamically adjust the difficulty level. Furthermore, it changes player and game parameters, saved in the settings log, to produce a new level of play. In this study, the virtual environment system can interact with players.

Second, the change in difficulty is designed using the artificial fog model, where the thickness can be calculated according to a heterogeneous distribution. This artificial haze can prevent players from recognizing objects that must be collected as part of the learning mission that must be achieved. Third, synthetic agents can be used to test the system for difficulty level changes, making it easier to analyze and more comfortable to fix.

Several sections of this research describe the development, testing, and analysis of file systems. Section III discusses the introduction to the dynamic difficulty adjustment, the activity theory serious-game model, the dynamic difficulty adjustment model, the artificial fog model and the application of synthetic agents. Furthermore, the experimental results and the discussion are shown in Section IV, while Section V concludes the research.

III. Dynamic Difficulty Adjustment

The dynamic difficulty adjustment process was carried out using parameters at an entry-level. When players increase or decrease a specific parameter, they have new values, which add to the old one to create a new parameter. Therefore, from new parameters, the game starts a new level, which splits its parameters into HVHL and LVHL. HVHL represents higher value parameters used to determine health and score. A player with high health and score is tagged better; hence the difficulty level should be adjusted. LVHL reflects a parameter that indicates a better player for a higher value [32]. This parameter is increased when the player solves a game problem quickly. Table I shows the game's parameters. Curriculum and the Education Unit Level Curriculum[49], as shown in Table II.

Compute each parameter's value by determining the skill value (efF_i), which is determined using equation (1). It calculates the player's performance, which is dependent on the current achievement parameter (F_{val_i}), the maximum (F_{max_i}), and the minimum (F_{min_i}) values.

Measure the overall player value and enemy's skill to specify the total amount (ef), the player or opponents abilities using equation (2). Equation (2) includes the weight of each parameter. The value serves as the significance of a parameter used to define the players' performance, as shown in Table III. For a detailed explanation, please refer to [14]–[19].

$$efF_i = \begin{cases} \frac{F_{val_i} - F_{min_i}}{F_{max_i} - F_{min_i}} & for\ HVHL \\ \frac{F_{max_i} - F_{val_i}}{F_{max_i} - F_{min_i}} & for\ LVHL \end{cases} \quad (1)$$

$$ef = \frac{\sum_{i=1}^{n}(efF_i * weight_i)}{\sum_{i=1}^{n} weight_i} \quad (2)$$

Analyze the skill values of the player and the opponent ($diff\ ef$) to determine whether the change is necessary using equation (3). The efp and denotes the player's and the enemy's skill value, which is measured using equation (2).

$$diff\ ef => p_{lim} * efp \quad (3)$$

Compute the arrangement value and replace the opponent parameters. The game parameters are modified using equations (4) and (5).

$$adj\ Fi = \begin{cases} diff\ ef * (Fmax_i - Fmin_i) & for\ HVHL \\ -diff\ ef * (Fmax_i - Fmin_i) & for\ LVHL \end{cases} \quad (4)$$

$$Fval_{0,i} = \begin{cases} FvalOld_{0,i} + adjF_i & for\ efp > efo \\ FvalOld_{0,i} - adjF_i & for\ efp < efo \end{cases} \quad (5)$$

$adj\ Fi$ and $Fval_{0,i}$ denote the appropriate value and current modification values of the players. This indicates that the device lowers the skills of players' previous opponent and attributes $Fval_{0,i}$ for them to beat the enemy more efficiently. The method is continuously used until the players have solved all problems or their health points equal zero.

A. Activity Theory Model Serious-Game

The gameplay consists of 6 steps, as shown in Fig. 1. In phase 1, the player is asked to take action by customizing the avatar or choosing the model after entering the game through its configuration section. Furthermore, in phase, players learn how to play and assess the game based on the activity model. In phase 3, they face the choice to choose a new mission or continue with the old one. When players select a new task, they play a puzzle, and when they decide not to select a new mission, the game system provides suggestions. The puzzle played in phase 4 consists of the tool in the form of tiles. The game's goal is to visualize the changes in the value achieved. Students perform tasks to fulfil missions, overcome challenges to remember knowledge, and focus on work.

Furthermore, in phase 5, the game awards added values to determine additional player abilities and other bonuses. After receiving the award, players face another challenge, which is an opportunity to increase the rewards they have received until the maximum value is achieved. There are three sides of players on the activity theory model, namely the play, learning, and intrinsic instruction. The player seeks help to learn the game interface using a pre-installed tutorial. From a learning point of view, the player analyzes the device provided by the game in the form of suggestions. The intrinsic instruction process enables the player to demonstrate and provide the player with learning instructions. Game systems assess, measure performance, and give feedback to players. Phase 6 evaluates, appreciates and improves the performance [5], [9], [46], [50]–[52].

TABLE I. Game's Parameters

Subject	Group's Parameter	Process	Game's Parameter
Player	HVHL	Number of correct answers	Score
	LVHL	The time to fix the task	Action Time
Enemy	HVHL	Enemy knack to break the problem with distinct form of query	Strength
	LVHL	knack to resolve matter in restricted time	Velocity

TABLE II. Highest and Lowest Value of Each Parameter

No.	Attribute in-game	Value	
		Highest Value/Fmax	Lowest Value/Fmin
1.	Score	100	45
2.	Action Time	210	0
3.	Strength	100	45
4.	Velocity	250	0

TABLE III. Parameter's Weight

Parameter	Weight
Score/Strength	0.8765
Action Time/Velocity	0.1235

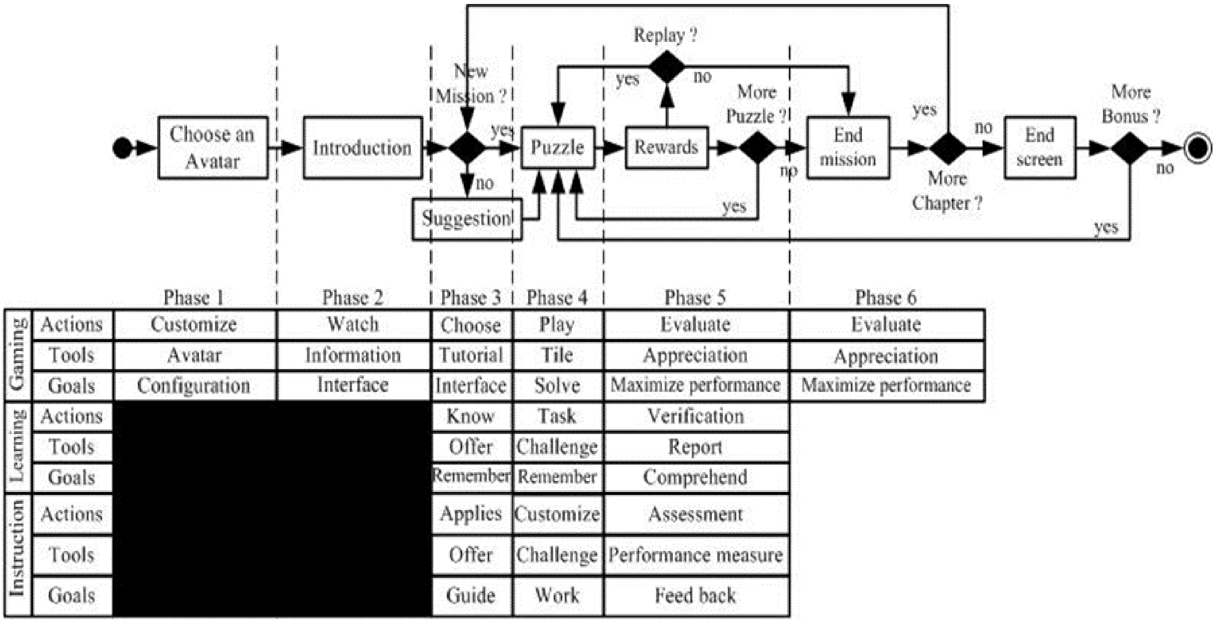

Fig. 1. Phases of Gameplay.

B. Dynamic Difficulty Adjustment Model

The process applied when the player successfully answers the question is analyzed in the dynamic difficulty adjustment model. There are four main processes in the application of FDDACP method in the game, these include 1) Collect Enemy's and Player's Attributes, 2) Adjust Level of Difficulty, 3) Change Enemy's and Player Attributes and 4) Save changes in Log. This process is shown in Fig. 2 [32].

C. Dynamic Difficulty Adjustment Model in Activity Theory Model Serious Game

Fig. 3 shows the mechanism of implementing the dynamic difficulty system in a serious game. This process is applied when the player fulfils the associated task. The proposed method in this research comprises the following six stages.

1) Read the initial parameter value of the player. This mechanism collects the entire parameter value before the player starts the game.

2) Player puzzle. After several times, the player receives the rewards, and the system reads the parameter value. This step processed the parameter value provided by the reward step and used it as input for the system adjustment method.

3) Adjust level using dynamic difficulty adjustment processes the parameter value provided by the 2nd step and calculates it to determine the mechanism.

4) The change of the player's parameter is carried out based on the adjustment value. For instance, if players are about to lose, the game gives them more time to answer the next question in peace.

5) Save Log Settings. This method saves the process of change in the game to see where the student needs change.

6) Create a new level. The change value is stored in the Log function to generate a new level.

When the player asks questions in the game, all processes above are completed. The next question will change the parameter as long as the player is safe.

D. Synthetic Fog Model

The use of synthetic foggy imagery aims to facilitate the creation of three-dimensional fog in a game. Therefore, changes can be made more measurable to reduce manufacturing time. The standard size of the PSNR and SSIM index is used to facilitate evaluation and comparison and a more detailed explanation can be seen in the reference [36][34]. Fig. 4 shows a different fog environment.

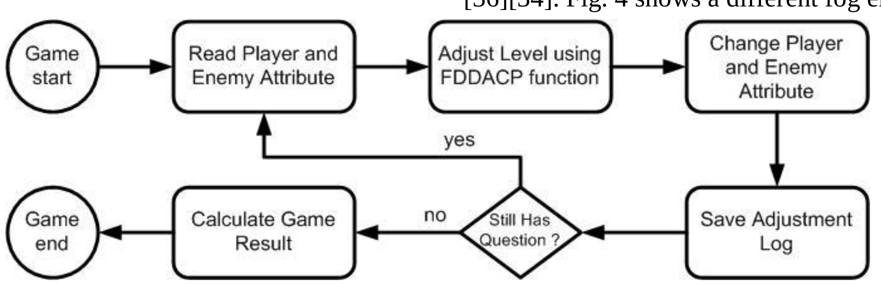

Fig. 2. Dynamic difficulty adjustment model.

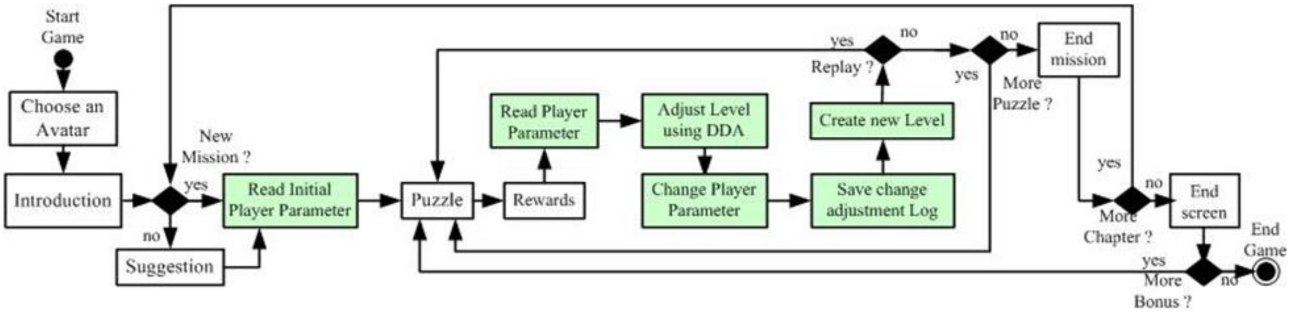

Fig. 3. Proposed dynamic difficulty adjustment in activity theory model serious-game.

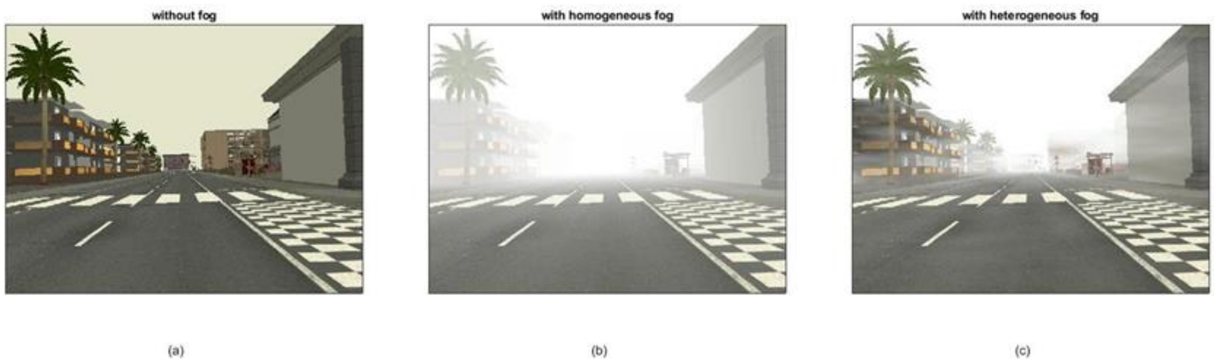

Fig. 4. The different fog environments. (a) No-Fog environment, (b) Homogeneous fog, (c) Heterogenous fog.

IV. Result and Discussion

A. Dynamic Difficulty Calculation

The results obtained from equations (1) to (6) are shown in Table IV. It comprises two scenarios, namely the enemy is lower and higher than the player. Therefore, for the first case, the parameter power was 1 (HVHL), and the speed was 100 (LVHL). This means that when the player reaches a score and time-act of 10 and 43, the game system will change, and in the next stage, the enemy's parameters increase hence the power and speed become 8.88 and 96.65. When the player's achievement is almost the same, the score becomes ten, and the time-act 40, hence the power parameter increases to 9.32, while the speed drops to 93.31.

Furthermore, in 2nd scenario, the enemy was higher with power and speed value of 15 and 30, while the player's achievement remained the same as in the previous scenario, at a score and time-act of ten and 43. When the power decreased to 13.62 and speed increased to 30.76, with the player's score, time-act, power and speed parameters of 10, 40, 10.08, and 32.11.

B. Synthetic Fog

This research used the score, time remaining, and player life parameters to determine the opponent's function in the game system. At the beginning of the game, players were not allowed to fight their opponents, but against time, score, and life, known as HVHL. The time remaining and the player's health are denoted with LVHL. The DDA changes the fog's thickness to hinder players from fulfilling the mission given. The fog used in this study is synthetic [36][34], as shown in Table V. Therefore, the thinner the fog, the lower the difficulty level generated, and the thicker the fog, the harder it becomes.

The haze is divided into ten parts, as shown in Table V. It starts from level 0 to 9, which denotes dense to extremely clear. In the game, fog level 0 (thick) means it is the most challenging, and 9 (extremely clear) denotes easy, as shown in Table VI.

TABLE IV. Example of The Game Scenario

Scenario 1st				**Scenario 2nd**			
Enemy = Low				**Enemy = High**			
HVHL	LVHL	HVHL	LVHL	HVHL	LVHL	HVHL	LVHL
Score	Time-act	Power (enemy)	Speed (enemy)	Score	Time-act	Power (enemy)	Speed (enemy)
10	43	1	100	10	43	15	30
10	40	8.88	96.65	10	40	13.62	30.76
		9.32	93.31			10.08	32.11

TABLE V. DIVISION OF FOG IN INTERNATIONAL VISIBILITY [36][34]

Haze level	Haze	Visibility
0	Dense fog	<50 m
1	Thick fog	50 - 200 m
2	Moderate fog	200 – 500 m
3	Light fog	500 m – 1 km
4	Thin fog	1 km – 2 km
5	Haze	2 km – 4 km
6	Light haze	4 km – 10 km
7	Clear	10 km – 20 km
8	Very clear	20 km – 20 km
9	Extremely clear	>50 km

TABLE VI. FOG/HAZE TYPE FOR EACH LEVEL IN THE GAME

Game level	Fog/Haze type
Level 1	Extremely clear
Level 2	Very clear
Level 3	Clear
Level 4	Light haze
Level 5	Haze
Level 6	Thin fog
Level 7	Light fog
Level 8	Moderate fog
Level 9	Thick fog
Level 10	Dense fog

C. Game Screenshot

The proposed game is shown in Fig. 5, where Fig. 5(a) is a screen belonging to the synthetic player, which comprises the time remaining, the achieved and target scores, the game difficulty level, and the synthetic player's life. Fig. 5(b) is the mission the synthetic player needs to complete, while Fig. 5(c) is the object to avoid. If the task can be accomplished, points will be added, while a decrease in the synthetic player's life is obtained when the object is held.

Fig. 6(a) and 6(b) represent the game's 3rd and 4th levels. The mission and object positions that must be avoided are visible in both figures. Fig. 7(a) and 7(b) show the 3rd and 5th levels of the game and its conditions. A thicker haze surrounds the game environment compared to Fig. 6(b). In Fig. 7(b), the mission positions to be reached and the objects to be avoided are increasingly invisible due to the thick fog.

Fig. 8(a) shows the 3rd level of the game, as illustrated in Fig. 6(a) and 7(a) It also shows the mission positions and objects to avoid. Meanwhile, Fig. 8(b) shows the condition when the game reaches the 9th level. Apart from the mission and invisibility of the objects to be avoided, the trees in front of the synthetic player also start to disappear.

D. Dynamic Difficulty Level Selection

The selection of dynamic difficulty levels is shown in Table VII. It indicates several different parameters owned by a synthetic player, such as score, student time, life, and health of the synthetic player. The following column shows changes in the level of difficulty with and without using DDA. The scoring parameter, remaining time and life of 12, 63 and 27 are shown in the third row. According to the settings based on DDA, with and without the game, levels are 3 and 2. The challenge increases with greater excitement when the player is at level 3.

Furthermore, when the score level drops on the scenario 4th to 10, the DDA will set the game level back to level 2. In contrast, in the settings without using the game level is increased to level 3 because it will undoubtedly cause players to feel frustrated and easily bored with the game.

Another example is seen in scenarios 7 to 10 in yellow highlight, where the setting with and without DDA determines the difficulty level to be 7 and 5 in green highlight, respectively. When the synthetic player score increases to 49 in red highlight, the setting uses DDA of the difficulty level rises to 8 in magenta highlight. Furthermore, the synthetic player score increases to 52 and 54 with the rise in the difficulty level to 10.

This is different from the difficulty level settings without DDA because when the synthetic player score is 35, the game system without DDA determines the difficulty level at 5 in green highlight. When synthetic player's score increase to 49, 52, and 54, the game difficulty level is suddenly raised to level 10 shown in grey highlight, which will lead to a sudden rise, frustrating the player and making them more reluctant to continue the game.

The phenomena in Table VII are graphically visualized, as shown in Fig. 9. The graph shows that the increase in the difficulty level using DDA is progressing, as indicated by the purple line.

A synthetic player is used to provide the advantage of testing many times without worrying about boredom. Fig. 10 is an experimental visualization of 10 repetitions, where each experiment is carried out 1,000 times to determine the difficulty/gameplay change.

TABLE VII. THE GAME LEVEL SELECTION COMPARISON

Scenario	Input Parameter			Game Level	
	Score	Time Remain	Player Life	DDA	without DDA
1	2	70	10	1	1
2	4	66	28	1	1
3	12	63	27	3	2
4	10	47	35	2	3
5	14	42	38	3	3
6	26	36	31	4	4
7	35	28	38	7	5
8	49	25	40	8	10
9	52	11	50	9	10
10	54	9	65	10	10

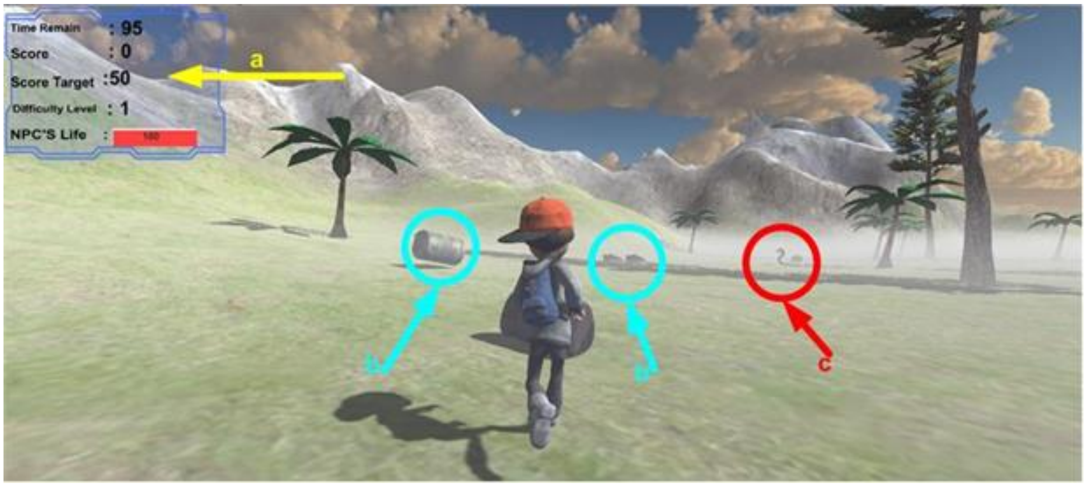

Fig. 5. (a) Panel belongs to synthetic players, (b) The mission to complete, (c) The object to avoid.

Fig. 6. The game screenshot: (a) The mission and the object in the 3rd level are still visible, (b) The mission and the objects are still visible in the 4th level.

Fig. 7. The game screenshot: (a) The mission and the objects in the 3rd level are still visible, the synthetic haze covers (b) The mission and the objects in the 5th level.

Fig. 8. The game screenshot: (a) The mission and the objects in the 3rd level are still visible, the synthetic haze covers (b) The mission and the objects in the 9th level.

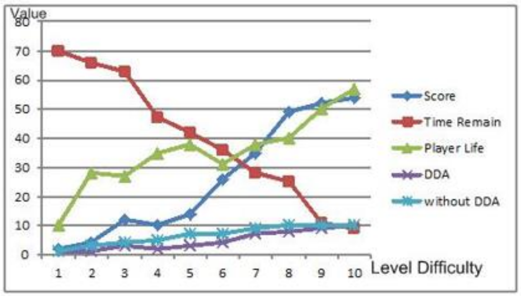

Fig. 9. The graph shows a gradual change in difficulty level.

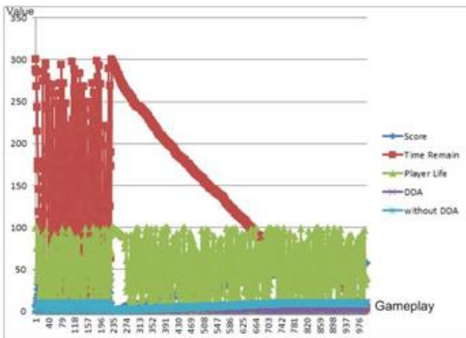

Fig. 10. The visualization of 1,000 times the difficulty level/gameplay change.

E. Comparison

This study produces a dynamic difficulty adjustment system applied to a serious game based on the activity theory model for educational material in 3D format. It differs in characteristics compared to the application of DDA in other studies. Table VIII shows these differences in detail with reference [32] to students and determining what has changed in enemy behaviour without implementing the serious-game model of activity theory. This is in accordance with the study by [27] on applying DDA in business and in-game. The study [48] is a study that focuses on setting up enemy formations in the 2-dimensional role play game genre. Adjustments are made based on variable difficulty curves and enemy variations of the fitness function. Preliminary study by [47] implements DDA using a ranking system to balance gameplay. When compared with the four studies, this research has similar characteristics [32]. However, the advantage of environmental changes resulting from DDA is applied in a serious-game-based activity theory model and tested using a synthetic player.

TABLE VIII. DIFFERENCE IN CHARACTERISTICS COMPARED TO THE APPLICATION OF DDA IN OTHER STUDIES.

References	**3D**	**Synthetic player**	**Environment change**	**DDA-ML**	**Education**	**Activity Theory Model Serious-Game**
[32]	-	-	-	√	√	-
[27]	-	-	-	-	√	-
[48]	-	-	-	√	-	-
[47]	-	-	-	√	-	-
proposed	√	√	√	√	√	√

V. CONCLUSION

In conclusion, this study proposed a dynamic difficulty setting system to overcome boredom and frustration when playing educational games. The game format selected is serious-game with an activity theory model, which details each goal into instruction, learning, and games. The serious-game comprises the same scope, namely action, equipment, and targets, making it easier to design a serious-game for specific and precise educational needs.

At the experimental stage, the serious-game system building was combined with a dynamic difficulty setting to obtain the players' abilities and skills. Furthermore, the limited visibility at different levels of difficulty led to the proposal of a 3D serious-game, which does not need the process of determining the characters in the early stages of the game. Designing a serious game for education determines the dynamic difficulty setting and educational content. The experimental results showed that the game system created can adjust the game environment smoothly.

Compared to previous studies, the system in this study has the advantage of using a serious-game model that focuses on improving student knowledge, involving smooth environmental changes, and avoiding competition with enemy characters. Besides, the proposed system is also able to follow the abilities of players who are not always the same.

Our next study is to add educational material settings for different player achievements. So not only setting the fog thickness but also considering the setting of educational materials. And we added artificial intelligence to make the changes more subtle.

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REFERENCES

[1] R. Tyagi, S. Vishwakarma, Z. S. Alexandrovich, and S. Mohammmed, “ICT Skills for Sustainable Development Goal 4,” in Quality Education, W. Leal Filho, A. M. Azul, L. Brandli, P. G. Özuyar, and T. Wall, Eds., Cham: Springer International Publishing, 2020, pp. 435–442. doi: 10.1007/978-3-319-95870-5_39.

[2] UNESCO & IESALC, “COVID-19 and higher education: Today and tomorrow. Impact analysis, policy responses and recommendations,” Iesalc, vol. April, no. 9, pp. 1–46, 2020.

[3] UNESCO, “The Futures of Education after COVID-19: Regional Dialogue,” 2020.

[4] UNESCO, “Distance learning strategies in response to COVID-19 school closures,” UNESCO COVID-19 Education Response Education Sector issue notes, no. April, pp. 1–8, 2020.

[5] M. R. Stevens et al., “Serious Games-Humanitarian User Research,” 2020.

[6] S. Skouw, A. Suldrup, and A. Olsen, “A serious game approach to improve food behavior in families—A pilot study,” Nutrients, vol. 12, no. 5, pp. 1–15, 2020, doi: 10.3390/nu12051415.

[7] M. Carvalho et al., “An activity theory-based model for serious games analysis and conceptual design,” Comput Educ, vol. 87, pp. 166-, 2015, doi: 10.1016/j.compedu.2015.03.023.

[8] M. B. Carvalho, "Serious Games for Learning : A model and a reference architecture for efficient game development," Universitas Degli Studi Di Genova, Technische Universiteit Eindhoven, 2016.

[9] M. Callaghan, N. McShane, A. G. Eguíluz, and M. Savin-Baden, "Extending the Activity Theory Based Model for Serious Games Design in Engineering to Integrate Analytics," International Journal of Engineering Pedagogy (iJEP), vol. 8, no. 1, p. 109, 2018, doi: 10.3991/ijep.v8i1.8087.

[10] K. Umam, M. Fachri, F. Nugroho, S. M. S. Nugroho, and M. Hariadi, "Serious game self-regulation using human-like agents to visualize students engagement base on crowd," Bulletin of Electrical Engineering and Informatics, vol. 11, no. 5, pp. 2717–2726, Oct. 2022, doi: 10.11591/eei.v11i5.3780.

[11] F. Nugroho, E. M. Yuniarno, and M. Hariadi, "An Environmental Domain Awareness for Serious-Game Using Perlin Noise Base Heterogeneous Haze Visualization," International Journal of Intelligent Engineering and Systems, vol. 15, no. 2, pp. 276–286, Apr. 2022, doi: 10.22266/ijies2022.0430.25.

[12] D. S. Lora Ariza, A. A. Sánchez-Ruiz, and P. A. González-Calero, "Towards Finding Flow in Tetris," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 11680 LNAI, no. Group 921330, pp. 266–280, 2019, doi: 10.1007/978-3-030-29249-2_18.

[13] M. Csikszentmihalyi, "The Flow, Psychologi & Happines," in The Flow, Psychologi & Happines, 2020, pp. 1–21.

[14] R. Burak Arslan and E. Filiz, "Enhancement of Player Experience in Video Games Using EEG Based Dynamic Difficulty Adjustment," in 2022 International Conference on INnovations in Intelligent SysTems and Applications (INISTA), 2022, pp. 1–4. doi: 10.1109/INISTA55318.2022.9894125.

[15] B. A. Aziz Hutama, S. W. Sihwi, and U. Salamah, "Kinect Based Therapy Games To Overcome Misperception in People With Dysgraphia Using Dynamic Difficulty Adjustment," in 2021 IEEE International Conference on Computing (ICOCO), 2021, pp. 230–235. doi: 10.1109/ICOCO53166.2021.9673556.

[16] P. Moschovitis and A. Denisova, "Keep Calm and Aim for the Head: Biofeedback-Controlled Dynamic Difficulty Adjustment in a Horror Game," IEEE Trans Games, p. 1, 2022, doi: 10.1109/TG.2022.3179842.

[17] D. ben Or, M. Kolomenkin, and G. Shabat, "DL-DDA - Deep Learning based Dynamic Difficulty Adjustment with UX and Gameplay constraints," in 2021 IEEE Conference on Games (CoG), 2021, pp. 1–7. doi: 10.1109/CoG52621.2021.9619162.

[18] T. Huber, S. Mertes, S. Rangelova, S. Flutura, and E. André, "Dynamic Difficulty Adjustment in Virtual Reality Exergames through Experience-driven Procedural Content Generation," in 2021 IEEE Symposium Series on Computational Intelligence (SSCI), 2021, pp. 1–8. doi: 10.1109/SSCI50451.2021.9660086.

[19] F. Özkul, D. E. Barkana, and E. Masazade, "Dynamic Difficulty Level Adjustment Based on Score and Physiological Signal Feedback in the Robot-Assisted Rehabilitation System, RehabRoby," IEEE Robot Autom Lett, vol. 6, no. 2, pp. 447–454, 2021, doi: 10.1109/LRA.2020.3046353.

[20] V. M. Á. Pato and C. Delgado-Mata, "Dynamic Difficulty Adjusting Strategy for a Two-player Video Game," Procedia Technology, vol. 7, pp. 315–321, 2013, doi: 10.1016/j.protcy.2013.04.039.

[21] S. Xue, M. Wu, J. Kolen, N. Aghdaie, and K. Zaman, "Dynamic Difficulty Adjustment for Maximized Engagement in Digital Games," Dec. 2017, pp. 465–471. doi: 10.1145/3041021.3054170.

[22] R. Hunicke and V. Chapman, "AI for dynamic difficulty adjustment in games," Challenges in game artificial intelligence AAAI workshop, vol. 2, Dec. 2004.

[23] A. Ebrahimi and M.-R. Akbarzadeh-T, "Dynamic difficulty adjustment in games by using an interactive self-organizing architecture," in 2014 Iranian Conference on Intelligent Systems (ICIS), 2014, pp. 1–6. doi: 10.1109/IranianCIS.2014.6802557.

[24] M. Weber and P. Notargiacomo, "Dynamic Difficulty Adjustment in Digital Games Using Genetic Algorithms," in 2020 19th Brazilian Symposium on Computer Games and Digital Entertainment (SBGames), 2020, pp. 62–70. doi: 10.1109/SBGames51465.2020.00019.

[25] M. Zohaib, "Dynamic Difficulty Adjustment (DDA) in Computer Games: A Review," Advances in Human-Computer Interaction, vol. 2018, p. 5681652, 2018, doi: 10.1155/2018/5681652.

[26] C. Liu, P. Agrawal, N. Sarkar, and S. Chen, "Dynamic Difficulty Adjustment in Computer Games Through Real-Time Anxiety-Based Affective Feedback," Int J Hum Comput Interact, vol. 25, no. 6, pp. 506–529, 2009, doi: 10.1080/10447310902963944.

[27] D. Kristan, P. Bessa, R. Costa, and C. V. de Carvalho, "Creating competitive opponents for serious games through dynamic Difficulty adjustment," Information (Switzerland), vol. 11, no. 3, 2020, doi: 10.3390/info11030156.

[28] A. Sarkar and S. Cooper, "Inferring and Comparing Game Difficulty Curves using Player-vs-Level Match Data," in 2019 IEEE Conference on Games (CoG), Aug. 2019, pp. 1–4. doi: 10.1109/CIG.2019.8848102.

[29] G. K. Sepulveda, F. Besoain, and N. A. Barriga, "Exploring Dynamic Difficulty Adjustment in Videogames," IEEE CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies, CHILECON 2019, 2019, doi: 10.1109/CHILECON47746.2019.8988068.

[30] M. D. B. S. Supriyadi, S. M. S. Nugroho, and M. Hariadi, "Fuzzy coordinator based ai for dynamic difficulty adjustment in starcraft 2," Proceeding - 2019 International Conference of Artificial Intelligence and Information Technology, ICAIIT 2019, pp. 322–326, 2019, doi: 10.1109/ICAIIT.2019.8834540.

[31] T. Constant and G. Levieux, "Dynamic difficulty adjustment impact on players' confidence," Conference on Human Factors in Computing Systems - Proceedings, 2019, doi: 10.1145/3290605.3300693.

[32] B. S. Avi Shena, B. Sitohang, and S. A. Rukmono, "Application of Dynamic Difficulty Adjustment on Evidence-centered Design Framework for Game Based Learning," Proceedings of 2019 International Conference on Data and Software Engineering, ICoDSE 2019, 2019, doi: 10.1109/ICoDSE48700.2019.9092725.

[33] J. Xiao, M. Shen, J. Lei, J. Zhou, R. Klette, and H. G. Sui, "Single image dehazing based on learning of haze layers," Neurocomputing, vol. 389, pp. 108–122, 2020, doi: 10.1016/j.neucom.2020.01.007.

[34] S. Haouassi and D. Wu, "Image dehazing based on (CMTnet) cascaded multi-scale convolutional neural networks and efficient light estimation algorithm," Applied Sciences (Switzerland), vol. 10, no. 3, pp. 1–21, 2020, doi: 10.3390/app10031190.

[35] C. O. Ancuti et al., "NTIRE 2020 challenge on nonhomogeneous dehazing," IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, vol. 2020-June, pp. 2029–2044, 2020, doi: 10.1109/CVPRW50498.2020.00253.

[36] X. Min et al., "Quality Evaluation of Image Dehazing Methods Using Synthetic Hazy Images," IEEE Trans Multimedia, vol. 21, no. 9, pp. 2319–2333, 2019, doi: 10.1109/TMM.2019.2902097.

[37] S. Ariyurek, A. Betin-Can, and E. Surer, "Automated Video Game Testing Using Synthetic and Human-Like Agents," IEEE Trans Games, pp. 1–1, 2019, doi: 10.1109/tg.2019.2947597.

[38] S. Ariyurek, A. Betin-Can, and E. Surer, "Automated Video Game Testing Using Synthetic and Humanlike Agents," IEEE Trans Games, vol. 13, no. 1, pp. 50–67, 2021, doi: 10.1109/TG.2019.2947597.

[39] S. Kotnana, D. Han, T. Anderson, A. Züfle, and H. Kavak, "Using Generative Adversarial Networks to Assist Synthetic Population Creation for Simulations," in 2022 Annual Modeling and Simulation Conference (ANNSIM), 2022, pp. 1–12. doi: 10.23919/ANNSIM55834.2022.9859422.

[40] B. Mucenic, C. Kaligotla, A. Stevens, J. Ozik, N. Collier, and C. Macal, "Load Balancing Schemes for Large Synthetic Population-Based Complex Simulators," in 2021 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW), 2021, pp. 985–988. doi: 10.1109/IPDPSW52791.2021.00156.

[41] C. Kiourt and D. Kalles, "Using opponent models to train inexperienced synthetic agents in social environments," in 2016 IEEE Conference on Computational Intelligence and Games (CIG), 2016, pp. 1–4. doi: 10.1109/CIG.2016.7860409.

[42] S. Juniastuti, M. Fachri, F. Nugroho, S. M. S. Nugroho, and M. Hariadi, "Crowd evacuation navigation for evasive maneuver of brownian based dynamic obstacles using reciprocal velocity obstacles," Bulletin of

Electrical Engineering and Informatics, vol. 11, no. 4, pp. 2187–2195, Aug. 2022, doi: 10.11591/eei.v11i4.3806.

[43] E. Lach, “A quick method for dynamic difficulty adjustment of a computer player in computer games,” Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science), vol. 9120, pp. 669–678, 2015, doi: 10.1007/978-3-319-19369-4_59.

[44] E. Lach, “Dynamic difficulty adjustment for serious game using modified evolutionary algorithm,” Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 10245 LNAI, no. November, pp. 370–379, 2017, doi: 10.1007/978-3-319-59063-9_33.

[45] E. Lach, “New adaptations for evolutionary algorithm applied to dynamic difficulty adjustment system for serious game,” Advances in Intelligent Systems and Computing, vol. 659, no. November 2017, pp. 492–501, 2018, doi: 10.1007/978-3-319-67792-7_48.

[46] Y. Zhonggen, “A Meta-Analysis of Use of Serious Games in Education over a Decade,” International Journal of Computer Games Technology, vol. 12, no. 1, pp. 36–43, 2020, doi: 10.1155/2019/4797032.

[47] A. Sarkar and S. Cooper, “Evaluating and Comparing Skill Chains and Rating Systems for Dynamic Difficulty Adjustment,” Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, vol. 16, no. 1, pp. 273–279, 2020.

[48] P. W. Atmaja, Sugiarto, and E. P. Mandyartha, “Difficulty Curve-Based Procedural Generation of Scrolling Shooter Enemy Formations,” J Phys Conf Ser, vol. 1569, no. 2, 2020, doi: 10.1088/1742-6596/1569/2/022049.

[49] A. Nur, R. T, and S. Habibah, “The Curriculum Development Based on the Indonesian National Qualification Framework,” Dec. 2019. doi: 10.2991/icamr-18.2019.60.

[50] D. B. Palhano, L. S. Machado, and A. A. F. Almeida, “Identifying Player Personality via a Serious Game A Pilot Study Using Item Response Theory,” Proceedings of SBGames, pp. 575–578, 2019.

[51] M. A. Camilleri and A. C. Camilleri, “Student-Centred Learning Through Serious Games,” INTED2019 Proceedings, vol. 1, pp. 2043–2052, 2019, doi: 10.21125/inted.2019.0578.

[52] F. G. M. Silva, “Practical methodology for the design of educational serious games,” Information (Switzerland), vol. 11, no. 1, pp. 1–13, 2020, doi: 10.3390/info11010014.