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An Adaptive Learning Game for Autistic Children using Reinforcement Learning and Fuzzy Logic

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Abstract
This paper presents an adapted serious game for rating the social ability in children with autism spectrum disorder (ASD). The required measurements are obtained by challenges of the proposed serious game. The proposed serious game uses the reinforcement learning concepts for being adaptive. It is based upon fuzzy logic to evaluate the social ability level of the children with ASD. The game adapts itself to the level of the autistic patient by reducing or increasing the challenges in the game via an intelligent agent during the play time. This task is accomplished by making more elements and reshaping them to a variety of real world shapes and re-designing their motions and speed. If the autistic patient's communication level grows during the playtime, the challenges of game may become harder to make a dynamic procedure for evaluation. At each step or state, using fuzzy logic, the level of the player is estimated based on some attributes such as the average of the distances between the fixed points gazed by the player or the number of the correct answers selected by the player divided by the number of the questioned objects. This paper offers the usage of dynamic AI difficulty system proposing a concept to enhance the conversation skills in the autistic children. The proposed game is tested by participation of 3 autistic children. Each one of them play the game in 5 turns. The results obtained display that the method is useful in a long time period.

Keywords: *Autism Spectrum Disorder; Adaptive Game; Reinforcement Learning; Fuzzy Logic.*

1. Introduction

Autism Spectrum Disorder (ASD) is a neuro-developmental sickness [1], which affects the social and communication skills. People with ASD have steady interests and repeated behaviors [2].

Unity of gene changes or environmental causes may influence the early brain development. In spite of the fact that autism is founded on the early brain development period, the symptoms are mostly blended at the age of two or three years old.

Currently, about 1% of the world population is stricken with ASD [3]. The identified prevalence of ASD in the United States is displayed in table 1.

Table 1. Identified prevalence of ASD in the US [4].

Surveillance Year	Birth Year	Prevalence per 1000 Children (Range)	This is about 1 in x children…
2000	1992	6.7(4.5-9.9)	1 in 150
2002	1994	6.6(3.3-10.6)	1 in 150
2004	1996	8.0(4.6-9.8)	1 in 125
2006	1998	9.0(4.2-12.1)	1 in 110
2008	2000	11.3(4.8-21.2)	1 in 88
2010	2002	14.7(5.7-21.9)	1 in 68
2012	2004	14.6(8.2-24.6)	1 in 68

The data was gathered through the Autism and Developmental Disabilities Monitoring (ADDM) Network from 2000 to 2012 [4]. ASD will signify the problem in the society serving as the main purpose of this work.

The efforts made by psychologists are concentrated on working and enhancing the functional autonomy skills. Specialists in the area of ASD are increasingly unifying technology in the sessions carried out with these people. With regard to technology, enhancements are being obtained in their autonomy skills [5].

Nowadays, technology is being used in various fields such as diagnosis and therapy of ASD. Learning through playing for young children is an accepted concept by the world [6]. Research works also show that children with ASD are naturally visual learners. This means that their learning through the vision-based method is the best among many other methods [7].

In addition to the traditional therapy methods, there are two kinds of technological solutions. They are being spread out as a compliment to influence the social and communication skills. These solutions are categorized as Hardware systems and Software solutions. The leaning of the hardware systems is addressed to the evolution of robots or toys with which autistic people can interact to reinforce their communication [8, 9].

The goal of a majority of software solutions is to promote communication [10] and distinguish emotions [11]. These systems normally combine support for audio, images, and text, thus allowing the users to plan sentences easily. Amid the software solutions, parts of the attempts are concentrated in the design and evolvement of computer games meant for these people [12].

Computer games grant positive impacts on people with ASD [13]. These games use emotions, language skills, and subjects like planification [I4, 15]. On top of these solutions, there is another type of research work concentrating on evaluating and analyzing the gaze of people with ASD when they study a social situation.

This method is based upon recording the point where a person fixes or the sweeping of his or her gaze. In order to analyze the way people with ASD evaluate the social situations, both the dynamic and static studies has been performed. By means of these studies, it has been tested how people with ASD do a lower fixation in the eye area but concentrate more on the mouth [16, 17]. This is an indicator of the difficulty exhibited by these people in the case of understanding social situations.

Serious video games with therapeutic goals are designed for autistic children under specific categories. The games could be either touchless or classic video games that require a gamepad or any appliances.

"Happy Candy" is the game designed for the paper. In this game, the mentioned distance is used. Also a selection of the objects of the game desired by the child is analyzed. Happy Candy would adapt itself to the level of the autistic child by reducing or increasing the challenges of the game. Happy Candy achieves this by easing the artificial intelligence-based level of difficulty of the game or making that harder. This can be used to help the diagnosis of future medical care. This also presents a credible support to make the most benefits of therapy meetings with its self-adaptive concept. For proof and validation, the medical and psychological estimation staff may be used to grade the results of the applications for this model.

The rest of this paper is organized as what follows. Section 2 presents a review on the related works. Section 3 explains the design of the system of the proposed technique and proposes the game. Section 4 describes how the game adapts itself to the level of a player. Section 5 displays and reviews the experiments. Finally, Section 6 concludes the paper and describes the future work.

2. Related works

In this section, we review the related works from two aspects. First we discuss the ASD-related research works, and then provide a survey on the research works related to serious games designed for the therapy of people with ASD.

2.1 Autism spectrum disorder (ASD)

ASD is a more suitable expression than autism. It stands for a group of compound disorders of brain development [18]. The signs of ASD contain unusual behavior in social communication, imagination, and interaction [19]. Based on Diagnosis and Statistical Manual of Mental Disorders (DSM-V), it is known that there are distinctive kinds of ASD despite the fact that they are diagnosed under the same category [20]. Under the current medical conditions, the reason for ASD is not yet very clear.

2.2. Serious games

Serious games can be clarified as a gaming technology that investigates the educational, therapeutic, and social influences [21]. Solving a problem such as training surgeon or accelerating learning progress is the main goal of designing serious games.

G. Khayat *et al.* [22] have recommended a serious game system for children with learning disabilities. This system aims at children of the age range 3–7.

A. Elmaghraby *et al.* [23] have proposed a framework that merges serious games with health informatics. It provides an environment for games that can help to enhance lifestyle, and provides a more friendly health diagnostics and treatments when possible.

Electroencephalogram (EEG) is typically used in ASD diagnosis or treatment progress but designing EEG-based serious games to gather neuro-feedback from ASD and some other developments might cause disarranges [24]. The brain states can be successfully identified between a range of efficiencies and accuracies; however, the system needs to wear EEG reading cap or electrodes, which is neither comfortable nor convenient.

Using EEG and Electrooculography (EOG), the eye gaze movement of a normal player could be used to control the movement of the playable character of that game [25]. The idea of using this method for autistic children could be remarkable notwithstanding the fact that using EEG is not comfortable for these children.

Bartolome *et al.* [26] have proposed a serious game that should be played on three levels with the attendance of an expert person. Their game involves some geometric shapes, and in the second level, candy-shaped elements appear for measuring the gaze of children with autism; they use the eye tracker technology.
Yi Li *et al.* [27], for the first time, introduced the concept of an adaptive game for autistic children. They gathered information about the child behavior using the Microsoft Kinect platform and Kinect games. They adapted the game when the child was sad or happy by facial recognition.

3. System design and serious game

The challenges of the game and how the child answers them are helpful to recognize the level of the child in a social manner. Adapting the game to the user's level would help the children to have a better entertainment. This may help the user to improve the communication level through the games run-time.

Happy Candy includes some dynamic levels. It begins with a rooky level consisting of certain simple geometric shapes. The player must select the shape when s/he is being questioned. Figure 1 displays the rooky level of the Happy Candy.

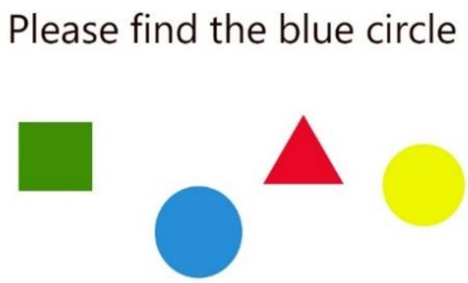

Figure 1. The rooky level of Happy Candy.

The player must take this level in some epochs. Using Reinforcement Learning (RL) algorithms, the game decides whether the player should pass the level and go to the next one or should go to the lower level. At any time, the level of the player will be calculated using Fuzzy logic. This calculation uses some attributes such as the average of the Euclidean distances between the coordination of the fixed points that the player has gazed and coordination of the questioned objects or the number of correct answers selected divided by the number of questioned objects.

4. Adaptive behavior

Massoudi *et al.* [28] have proposed a method that helps the players of video games to have a better experience of gaming. They proposed the Dynamic AI Difficulty of the game. Their proposed method involves the implementation of a tower defense game. Using fuzzy logic, the game finds the appropriate difficulty for the player and adapts itself to the level of the player. Eventually, the player will experience more entertainment than other conventional games.

The dynamics of the AI difficulty system of this method is achieved by recording the history of certain prominent parameters, which shows the player's level during play time. Using fuzzy logic, it measures the player location in the autism spectrum.

An intelligent serious game can adapt itself to the player's communication level using reinforcement learning. In Happy Candy, the elements have an AI agent, which increases or decreases the challenges of the game. At first, the elements are only simple geometric shapes. During the playtime and based on the player's level, the AI agent decides to harden or ease the game by increasing or decreasing the number of elements, re-shape them to a variety of real-world shapes, re-designing their motions, and altering their speeds. Figure 2 displays a medium level of Happy Candy. The player must pick the requested shape correctly to reach the next level.

Figure 2. Examples of shapes in a medium level of Happy Candy.

The automata used by the AI agent for adaptation is shown in figure 3. The agent selects the most suitable action in each step based on the automata.

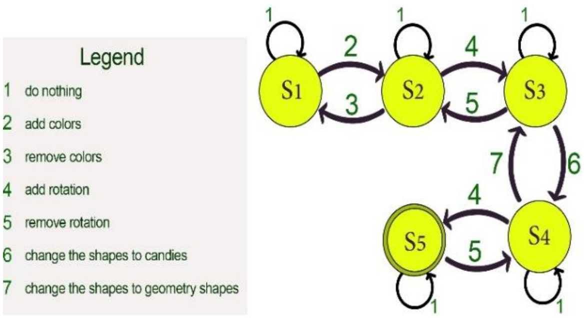

Figure 3. Automata of the proposed game.

The game is implemented by unity engine.

The following sections consist of the implementation of reinforcement learning and demonstration of the application of fuzzy logic in this method.

4.1. Find the best actions in each state

An artificial intelligent agent should have the power of perceiving information about its environment, which is called Machine Learning in computer science. There are three major paradigms of machine learning. They are called Supervised Learning, Unsupervised Learning, and Reinforcement learning. The latter is appropriate for an adaptive behavior in a dynamic environment. In this work, the reinforcement learning was used to obtain the adaptive behavior [29].

Supervised learning is learning from the examples provided by a knowledgeable external supervisor. However, in reinforcement learning, the agent must know how to map situations to actions, and must be able to learn from its own experience. The agent is not told which actions to take but instead, has to try the actions and discover which actions yield the best reward. In most cases, actions may affect not only the immediate reward but also the next state, and through that, all future rewards.

Consider an agent interacting with its environment to achieve a goal. That agent must be able to sense the state of its environment, and must be able to take actions that affect that state. The goal(s) of the agent must be based on the state of its environment [30].

Reinforcement learning problems are mainly modeled in a Markov Decision Process (MDP). Figure 4 displays how an agent interacts with its environment in the MDP model.

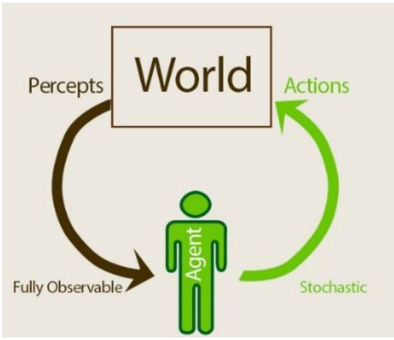

Figure 4. Markov Decision Process Model.

In situations where the decision-maker is under uncertainty, MDP can provide a mathematical model for decision-making in that situation. MDP is displayed by a tuple with four elements (S, A, P, R) [30]:

1. S : Set of probable states for an agent.
2. A : An action space displaying all the possible actions the agent can do.
3. $P: S \times A \times S \rightarrow [0,1]$, which is a random transition function displaying the probability of transitioning to state 's'' from state 's' by choosing action 'a'.
4. $R: S \times A \times S \rightarrow R$ which is a reward function displaying the feedback the agent

gets from the environment after transitioning from state 's' to state 's'' by choosing action 'a'.

In MDP, an agent at each state has a set of actions, which is a subset of all possible actions in the agent's action space. The purpose of all the reinforcement learning-based algorithms is to find an optimal policy that can detect the most valuable actions at each state based on MDP.

State-Action-Reward-State-Action (SARSA) is an algorithm for learning an MDP policy. SARSA reflects the fact that the main function for updating the Q-value (value of a state-action pair) depends on the following parameters, the first parameter being the current state of the agent "S_1". Then the agent chooses action "A_1" and "R" is the reward that the agent gets for choosing action "A_1". The next parameter is the state "S_2" that the agent will now be in after taking action "A_1". Finally, in the next action, "A_2", the agent will choose in its new state, taking every letter in the quintuple $\left(s_t,\ a_t,\ r_t,\ s_{t+1},\ a_{t+1}\right)$ [30].

SARSA is one of the most typically used reinforcement learning algorithms in video games. As Massoudi *et al.* [28] have explicated, SARSA uses (1) to rate every state-action pair:

$$Q\left(s_{t-1},a_{t-1}\right) = (1-\alpha)\, Q\left(s_{t-1},a_{t-1}\right) + \alpha\left(r+\gamma Q\left(s_t,a_t\right)\right) \qquad (1)$$

At each time step 't', the value of a state-action pair $Q\left(s_{t-1},a_{t-1}\right)$ is specified. s_{t-1} is the previous state where the agent had been, and a_{t-1} is the action he selected at that state.

$$r = Correct\_ans_{current} - Correct\_ans_{last} \qquad (2)$$

The r value in the formula is the prompt reward that the agent gets from the environment after transitioning from state s_{t-1} to state s_t by choosing action 'a_{t-1}'. It is calculated by a difference between the number of current correctly answered questions and the number of correctly answered questions until the last epoch.

$\gamma(0 \le \gamma \le 1)$ is the discount factor that displays the affection of future actions on the value of the selected action at the current state. This parameter shows that the value of each state-action pair is specified regarding its future outcomes.

$\alpha(0 \le \alpha \le 1)$ is the learning rate, which displays the affection of agent's previous experiences from the environment on rating each state-action pair. To obtain the optimal policy, we always select the most valuable $Q\left(s_t,a_t\right)$ in (1) to rate $Q\left(s_{t-1},a_{t-1}\right)$.

A technique that chooses the best actions at each state with a higher probability is suggested. To attain this, using the SoftMax action selection method is helpful [28] but this action selection method is not appropriate for video game purposes because video games need diversity in their actions. However, SoftMax gives a little chance for lower-valued actions to be chosen. The diversity of actions in the game is important because it can increase the therapy factor of the game.

Action selection probabilities at each state are calculated linearly based on their values to gain a technique that can make good diversity in choosing actions and make the higher-valued actions to be chosen with higher probabilities. Three probability vectors are created for each state; each one of their elements shows the probability of selectable possible actions at that state. The first vector is $\vec{P_H}$; each one of its elements is computed based on (3):

$$\mathrm{P_H}\left(\mathrm{s},\mathrm{a_i}\right) = \frac{\mathrm{Q}\left(\mathrm{s},\mathrm{a_i}\right)-\left(\min-\varepsilon\right)}{\sum_{k=1}^{n}\left(\mathrm{Q}\left(\mathrm{s},\mathrm{a_k}\right)-\left(\min-\varepsilon\right)\right)} \qquad (3)$$

where, *min* = Minimum $(Q\left(s,a_1\right),Q\left(s,a_2\right),\ldots,Q\left(s,a_n\right))$, $\varepsilon > 0, a_i \in A_S, A_S \subseteq A, i = 1,2,3,...,n$ is the set including possible actions in state s, and A is the set of all actions in agent's state space. According to this formula, the action probabilities are calculated linearly based on their values. The *Min* value is taken into account as the origin of the vector. The element ε (that must be greater than zero) was added to the actions that had the lowest values. If ε was equal to zero when all the vector elements had the same values, there would be division by zero error. It is better for ε to be appointed a small value to have a low influence on the probability of choosing higher-valued actions.

Since the state-action pairs are rated, another probability vector, $\vec{P_E}$, could be created to select the lowest values with higher probabilities. Each element of $\vec{P_E}$ is calculated based on (4):

$$P_E(s,a_i)=\frac{(\max+\varepsilon)-Q(s,a_i)}{\sum_{k=1}^{n}\left((\max+\varepsilon)-Q(s,a_k)\right)} \quad (4)$$

where, max = Maximum $(Q(s,a_1),Q(s,a_2),\ldots,Q(s,a_n))$, $\varepsilon>0, a_i \in A_S,\ A_S \subseteq A, i=1,2,3,\ldots,n.$ Using this equation, the least valuable actions at each state with higher probabilities could be chosen linearly. There is another probability vector $\vec{P}_M$ for each state that has the same probability for all of its elements using (5):

$$P_M(s,a_i)=\frac{1}{n}\ ,\ i=1,2,\ldots,n \quad (5)$$

where, n is the number of total possible actions for an agent in state s. We use the three probability vectors $\vec{P}_H$, $\vec{P}_M$, $\vec{P}_E$ to obtain an adaptive behavior.

$\vec{P}_H$ is used for a hard difficulty as the intelligent agent who uses $\vec{P}_H$ probability vector always selects the best actions versus the player with higher probabilities. $\vec{P}_M$ is used for a medium difficulty, and all of the actions in this vector have the same possibility to be selected. $\vec{P}_E$ is used for an easy difficulty as the intelligent agent who uses the $\vec{P}_E$ probability vector always selects the least-valued actions with higher probabilities. Whenever a state action pair is updated by (1), these three vectors are recreated.

It is necessary to learn the player's level, and the game uses that to adapt the agent's behavior with the player's level. In the next section, the application of fuzzy logic for achieving an adaptive behavior is demonstrated [30].

4.2. Measuring player's level using fuzzy logic

The real life parameters are usually fuzzy. For example, it cannot be said for sure if the weather will be rainy or sunny tomorrow but it can be said that there will be a 70% chance of raining based on the information gathered from the weather prediction centers. Our problem is like the above-mentioned statement, i.e. it cannot be said for sure if a certain user is surely professional or amateur, which is the reason that fuzzy logic is used.

To measure the player's skill level, we established a parameter named SF (Skill Factor), which is calculated by (6) [26]:

$$SF=\frac{\sum_{i=1}^{n}w_i f_i}{\sum_{i=1}^{n}w_i} \quad \text{where } 0\le f_i\le 1,\ \ w_i>0 \quad (6)$$

f_i is a custom parameter specified arbitrarily to show the player's skills. Each f_i has to be a normalized value indicating the player's percentage of success in that skill. For example, to calculate the player's skill in accuracy through time, we can use:

$$f_i=\frac{ans}{tot} \quad (7)$$

where, ans = correct answers to the questioned elements and tot = total of the questioned elements during one epoch.

Figure 5 shows the fuzzy diagram used to measure the player's skill level according to the SF variable [28].

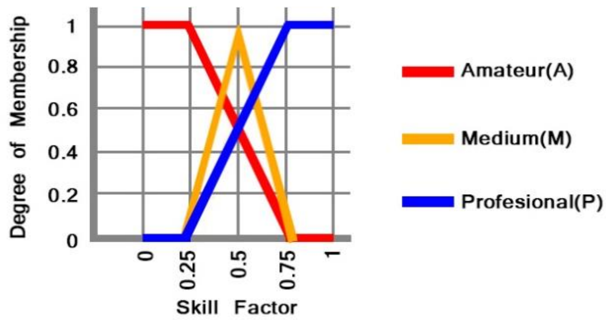

Figure 5. A fuzzy diagram presenting player's degree of membership to each set.

These parameters are updated dynamically during the playtime. They are used to measure the player's level. w_i is issued as the weight for every parameter f_i to show its influence on the computing SF. As w_i, we used "1 – *average*" of the distances between the gazing point of the player and the questioned elements during one epoch, which corresponds to SF. For measuring the player's communication level, the three sets P, M and A are specified. They describe the professional, medium, and amateur players, respectively.

We make a final action probability vector for each state using (8) to obtain an adaptive behavior based on the player's degree of membership to the specified sets:

$$\vec{P}_{final}=\mathrm{lerp}\left(\mathrm{lerp}\left(\vec{P}_E,\vec{P}_M,1-\mu_A(SF)\right),\vec{P}_H,\mu_p(SF)\right) \quad (8)$$

where μ_A and μ_p indicate the degree of membership to the sets A and P, respectively, and lerp is a linear interpolation function in programming languages.

Linear interpolation involves estimating a new value by connecting two known adjacent values with a straight line. If the two known values are (x_1, y_1) and (x_2, y_2), the linear interpolation is the straight line between these points. For a value x in the interval (x_1, x_2), the value y along the straight line is given by (9).

$$\frac{y-y_1}{x-x_1}=\frac{y_2-y_1}{x_2-x_1} \tag{9}$$

Solving this equation for y, which is the unknown value at x, gives (10).

$$y=y_1+(x-x_1)\frac{y_2-y_1}{x_2-x_1} \tag{10}$$

and the lerp function in programming languages calculates its return value by (11). This equation is based upon (10) and has three values as arguments: the coordination of the first point that we name $Value1$; next, the coordination of the second point, which we call $Value2$; and then the Weight of $Value2$ which, must be in the interval (0, 1).

$$\text{Value1}+\text{Weight}\times(\text{Value2}-\text{Value1}) \tag{11}$$

Notice that if the Weight equals zero, the return value would be $Value1$; and if it is equal to one, the return value of the function would be $Value2$.

Using linear interpolation secures that some of the P_{final} elements are always equal to one. P_{final} demonstrates the probability of selecting each action in state 's' based on the player's communication skills. By using it, the agent will take its best decisions regarding the player's communication skill level with higher probabilities. As all the parameters used in calculating P_{final} alter dynamically, the agent can constantly adapt itself with any changes occurring to the player's skills, so if the player's communication level grows during the playtime, the challenges of the game also get harder. This makes the technique as an especially dynamic therapy method for that patient. After choosing each action with probabilities determined in P_{final}, the selected actions will be rated repetitively with SARSA algorithm, and the system constantly attempts to adapt itself to the player's communication skill level [28].

5. Experiment

The experiment was carried out with participation of 3 autistic children. They used a laptop and a mouse pad for playing. The information about these children is shown in table 2.

Table 2. Information about the children who participated in the experiment.

Identifier	Gender	Age	Other disorders
Patient 1	female	9	none
Patient 2	male	16	deafness, echolalia
Patient 3	male	8	mental retardation

To estimate the player's skills, some parameters are required. The number of correct answers, the elapsed time of the game, and the stage that the game ends up are the necessary parameters to evaluate the player's skills.

Formula (12) is created based on these parameters:

$$p=(10\times S\times \text{correct}_{ans})-t \tag{12}$$

where S is the stage that the game ends up, t is the elapsed time of the game by the end, and p is the total point that indicates the user's skill rate during a turn of the game. Every participant played for 5 turns and the outcome data was demonstrated in figure 6.

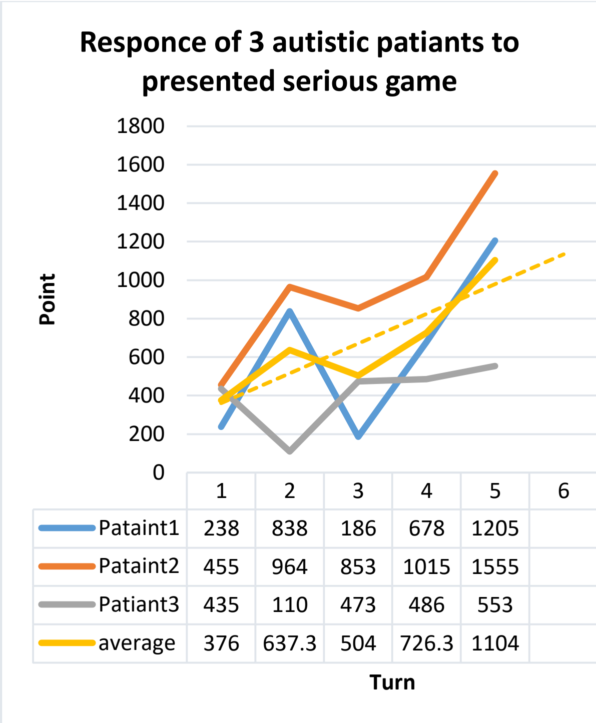

Figure 6. Response of 3 autistic patients to the presented serious game.

Based on this figure, the outcome is positive, and the proposed method might be useful for these children in a long time period.

6. Conclusion and future work

The social and communication skills are one of the most significant areas that affect ASD. People with ASD have problems interacting and having connections with people. This paper hardly attempts to build a system for people with this problem. Hopefully, using that system, they might have a better experience of life. It is also an attempt to study the way that people with ASD look through the objects and their motions.

The experiments display that this method and game might be helpful for these people, especially when the game is played in a long time period.

It is notable to mention that there were some deflects in this research work. First, the number of participants was very small. Secondly, these children played the game in a short time period. Also the children were not comfortable with the appliance of playing.

This game is adaptive and dynamic. Therefore, the game is a simulator of real life situations. This game is very helpful and positive towards these children's social skill improvement.

It will be necessary to investigate the development of the following areas: to develop new serious games associated with the social and communication areas and to identify new serious games that have a more complicated scenario, game play, and therefore, more intelligent agents.

A future game should be an infantine one and might have path finding or Swarm Intelligence methods to wise up to the AI of non-playable characters (NPC) for players with a higher level.

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نشریه هوش مصنوعی و داده کاوی

یک بازی انطباق‌پذیر آموزشی برای کودکان مبتلا به اوتیسم با استفاده از یادگیری تقویتی و منطق فازی

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چکیده:

در این مقاله، یک بازی جدی انطباق‌پذیر، برای اندازه‌گیری سطح مهارت‌های اجتماعی و کمک به درمان کودکان مبتلا به اختلالات اوتیسم، ارائه شده است. بازی از طریق یک عامل هوشمند مصنوعی و با استفاده از مفاهیم یادگیری تقویتی، اقدام به سخت یا آسان‌کردن چالش‌های بازی می‌نماید و سختی بازی متناسب با مهارت‌های کاربر تنظیم می‌شود. در هر مرحله یا حالت، سطح مهارت‌های کاربر بر اساس برخی از پارامترهای طراحی شده و با استفاده از منطق فازی، مشخص می‌شود. نسبت تعداد پاسخ‌های صحیح کاربر به تعداد کل سوال‌ها، نمونه‌ای از این پارامترها است. بازی با رشد سطح مهارت‌های اجتماعی کودک در حین انجام بازی، سخت‌تر می‌شود. با تغییر سطح بازی، یک فرآیند پویا برای ارزیابی کودک، شکل می‌گیرد. در نهایت در این تحقیق، مفهومی مناسب برای کمک به درمان کودکان مبتلا به ASD، ارائه شده است. بازی پیشنهادی مقاله، توسط ۳ کودک مبتلا به طیف اختلالات اوتیسم، آزمایش شده است. هریک از این کودکان در ۵ نوبت این بازی را انجام داده‌اند. نتایج به دست‌آمده نمایان‌گر موثر بودن این روش در بهبود کودکان مبتلا به اوتیسم است.

کلمات کلیدی: طیف اختلالات اوتیسم، بازی انطباق‌پذیر، یادگیری تقویتی، منطق فازی.