Customization of Contents for Acquisition of Skills of FPS without Trainer

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Abstract

In this paper, we conducted a study to develop self-study materials with the ability to provide more suitable materials for students' skills. A first person shooter (FPS) type simulator-based teaching material is created to acquire knowledge. Conventional games resume from a predetermined scene regardless of trainee's skill contributes to no increases in knowledge and skill. In this paper, we propose a re-spawning point suitable for each trainee by a recommendation algorithm which tries to find good game scenes by trial and error.

Keywords: Reinforcement Learning, E-Learning, Game AI, Virtual Reality.

1. Introduction

The role of E-learning is growing wider and wider every year, so better quality E-learning system is required for a wide variety of classrooms. The main issue of update of quality of E-learning is the quality of recommendation of contents which fit the student's skill. Some of E-learning curriculums need human support staff to re-offer the contents because the machine-selected contents are unfitted to the students. Therefore, self-study using by such a poor grade of E-learning curriculums is difficult.
We focus on the respawn point as the automatic content generation/recommendation of the video game based E-Learning. Response point is a game resuming point.
Generally speaking, there are some games which a player has to start the game from the beginning whenever a player fails the game along the way. In such a game, in sometimes a content that does not contribute to an increase in knowledge and skill is forced to be played. This paper attempts to propose a respawn point suitable for students' skill by using a recommended AI that gains experience while proposing a scene through trial and error.
This paper is organized as follows. In the next section, the FPS game as our text to learn is explained. We have to design the game like text in which whoever can learn new knowledge regardless of any skill and knowledge. So in this game-like text we adopt zombies, which everyone already know attack the player but there is no one who knows actual behavior. In the third section the algorithm to recommend a better response point for a student to expect to acquire the necessary knowledge and skill for its ability is proposed. The final result of the simple experiment by 20 university students is shown.

2. The E-learning text of FPS style which it can learn how to escape from zombie

2.1. *The overview of the E-learning*

This FPS text is made by Unity, a commercial 3D game design tool. Fig.1 illustrates the game field. Buildings of a high school are simulated in the cyber space.

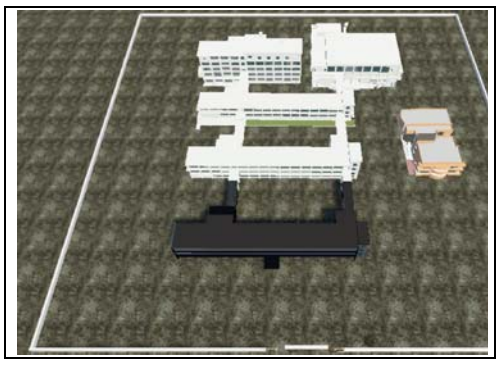

Fig.1 The FPS-like lesson field in cyber space

The site of the school is surrounded by walls and there is the only one gate to go to the outside from the inside of the school. 50 zombies are set around the gate. The avatar of the student starts from the farthest point from the gate and it aims to reach the gate. Zombies can know the location of the avatar precisely and they go toward to the avatar's current location. If a zombie collides the avatar a trial is over.

2.2. *"Respawn" and "Respawn point"*

As shown in Fig.2 a student uses this lesson material by First Person Shooter Style (FPS).

Fig.2 A scene of lesson

The operation of its avatar is done by moving the keyboard and changing the viewpoint by moving the mouse. One trial is to reach the gate of the entrance or get caught by the Zombie. When replaying, call the respawn to change the position of the player and zombies and start the game. The point or its corresponding scene is called the respawn point.

3. The proposed respawn algorithm

Here, the successful and unsuccessful attempts collected in advance are made into a database, and a respawn point that is easy to learn is generated. The respawn point is automatically generated in three stages after a play failure.(Step 1) First, select the teacher player by comparing the record of the player registered in the database and the student's play history. (Step 2) Next, select a successful play closest to the failed play from the history of the selected teacher player, and select a promising point as the respawn point from the initial state at the next trial. (Step 3) Update the value of the respawn point adopted according to the result of the trial.
The following briefly describes each of these steps.

3.1. *Step1: Selection of teacher player*

Compares the player-level data recorded in the database with the student data, and selects a teacher player. There are many methods can be thought. In our current system we adopt the maximum information gain approach. The teacher who can expect the largest information gain if the student can behave as it does is selected. The information gain uses KL divergence as follows.

$$KL(P||Q) = \sum_i P(i)\, log \frac{P(i)}{Q(i)} \qquad (1)$$

where P(i={success, failure}) is the ratio at which a given player has reached state i in the past from a given state and Q is the same ratio of the current student.
Figure 3 shows an example of this step of the selection of the teacher player, where 5 trial data each of players A and B are found in the database near the student's trials. In that case, therefore PA (i = success) = 3/5, PB (i = success) = 2/5, where the probability of A as the teacher of the student is high.

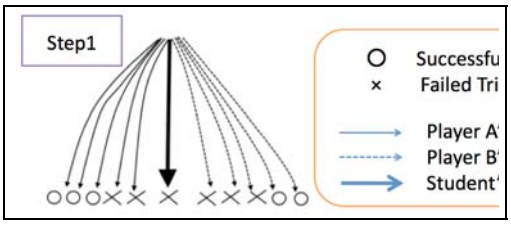

Fig.3 Step1 of Respawn algorithm

3.2. *Step2: Selection of Teacher's Successful Record*

In the step 2 firstly calculates the core point C. The core point is the intersection closest to the state of the student at the end of the play in the set of successful trials of the teacher player. Fig.4 shows an example.

Suppose now that the n-th play failed and ended. Here, it is assumed that C1 and C2 exist during the teacher's trials near the point E (n) at the end of the student's play. In this case C2 is the core point C(n) because the closest intersection C1 is belong to a failure trial.

3.3. *Step3:Learing of Content Recommendation Skills*

In the Step 3 the value of the selected respawn point is updated by using Temporal Difference Learning (TD learning) [2].

$$V\big(R(n)\big) \leftarrow V\big(R(n)\big) + \alpha[r_{n+1} + \gamma V(C(n+1) - V(R(n))] \quad (2)$$

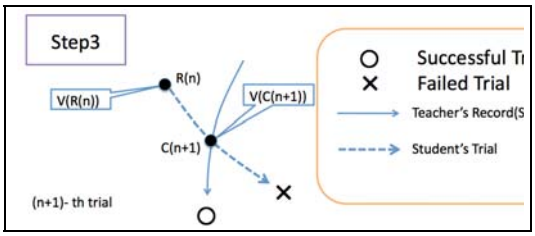

Fig.5 Step3 of Respawn algorithm

In Fig. 5, the value V(·) of the respawn point R (n) is updated at the (n + 1)-th play.
The point itself has the value V. This V will be higher if it contributes to the improvement of students' skills, and it will have a lower value otherwise. By learning this value through trial and error, it can be expected to select a respawn point where learning can be performed more efficiently.

4. Experiments

We actually played a simulator equipped with the proposed respawn algorithm.

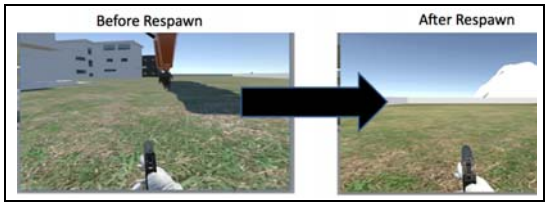

Fig.6 Result of the experiment

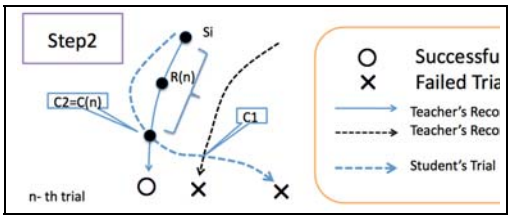

Fig.4 Step2 of Respawn algorithm

Fig. 6 shows the situations: the left figure shows the scene at the end of a trial after colliding with zombies and the right figure illustrates the scene of the respawn point recommended by the proposed algorithm. We confirmed the basic procedure of the algorithm well working.

5. Conclusion

In this paper, we developed a video game like teaching material using virtual space. We proposed a respawn algorithm that supports the efficient learning experience to acquire skills of the player.

References

1. G.N. Yannakakis, J. Togelius, Artificial Intelligence and Games, Springer, 2018.
2. H. Y anagimoto, S. Omatu, Information Filtering Using Kullback-Leibler Divergence,pp1147-1152, IEEJ Trans. EIS Vol.125, No.7, 2005.
3. R. S. Sutton, A. G. Barto, Reinforcement Learning: An Introduction, A Bradford Book,1998.