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Training System for Learning Tactics from E-sports Playing Video Based on Explanations

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Abstract: In e-sports, the play videos of skilled players are good learning materials for beginners who want to acquire and learn tactics. Tactics are a series of actions that are taken to accomplish various objectives in response to a situation. When learning tactics from videos, players need to select meaningful actions. However, discriminating whether actions are meaningful for forming tactics is difficult. Our research supports players who want to acquire the skills of identifying meaningful actions from playing videos because such actions have causal relations with each other. If players can explain the causal relations of the extracted actions, this ability suggests that they have indeed extracted appropriate actions. This paper constructs a system that gives a playing video that contains a scene with important tactics and provides an environment in which players can explain them in the video. It also gives feedback about the appropriateness of the extracted actions.

Keywords: tactics acquisition, play videos, e-sports, scene explanations, causal relations

1. Introduction

E-sports is an abbreviation for "electronic sports," a name that refers to computer games as athletic competitions. E-sports is attracting more and more attention each year, over 70 million people watch E-sports over the Internet or on television globally, and the number of people who annually compete in such activities is also growing (Jenny et al., 2017). In e-sports, players engage in competitions by repeatedly making decisions on actions based on the current situation. Appropriate actions are based on tactics that consist of objectives for the game situation and a series of actions based on the objectives. If players just know a few actions, they will struggle to choose actions that increase their chances of winning. To succeed, players must know many tactics beforehand.

Learning from skilled players is one method for acquiring tactics, although such opportunities are generally scarce for novice players. To solve the lack of teachers, several learning support systems provide the role of a teacher and impart knowledge instead of a human teacher (Melis, et al. 2004, Carbonell, 1984). These systems need to have the knowledge they teach as teaching materials. However, in the field of e-sports, the tactics taught are often implicit; general teaching materials do not exist.

As a preliminary step to teaching tactics, Yang et al. extracted tactics for a battle game. They modeled combat as a graph structure showing the interactions of characters in a game genre called Multiplayer Online Battle Arena (MOBA) and extracted winning patterns from the changes in graph features (Yang et al., 2014). In their graph structure, since links only represent defeats or attacks, the extracted winning patterns just denote a series of defeating or attacking actions. Their approach cannot be considered tactics because it fails to clarify what actions should be taken in response to situations.

Researches have addressed support for tactical acquisition in more conventional sports. For example, Nishida et al. developed a system that targeted tennis tactics that analyzes the position of the ball and each player from video and presents the next action as a tactic based on the analysis results and the tactical knowledge held by the system (Nishida et al., 2011). By looking at the information presented by this system, the next action in response to a situation can be acquired as a tactical move. However, even though some tactics consist of more than one action, this system only focuses on tactics comprised of just one action.

Since the sequences of human actions are an embodiment of tactics (Shikata et al., 2020), observing effective scenes of the videos of skilled players and extracting the action sequences contained in them might be a good method for acquiring tactics with several actions. Good, effective scenes consist of a series of actions, although not all actions necessarily constitute a tactic. Therefore, we must identify only the critical action sequences that form tactics. Extracting the action sequence and causal relationships between actions from playing videos is the same as explaining the good points of plays in the videos. Learning by explanation is regarded as one of the effective learning methods for organizing the acquired knowledge by (Aleven et al, 2002), so our research introduces the explanation for selecting the important actions to support players who want to acquire the skill of finding meaningful actions from playing videos.

Since critical actions lead to the achievement of objectives, a causal relationship exists between the selected actions and objectives. For example, when allies and enemies are rather far apart, the following action sequence, "*move closer to the enemy* and *attack at short range*," is an appropriate tactic because the latter action can be taken only in a situation that includes both allies and enemies, as derived by the former action. If the players can extract such action sequences, they will successfully acquire tactics. Our research constructs a system that provides playing videos that contain a scene with important tactics and an environment in which players can explain the tactics dramatized in the videos. In actions with causal relations, situations derived by the former action lead to the latter action. Therefore, the system gives feedback by judging whether the extracted action sequences have appropriate causal relationships.

2. Overall Framework of a Training System of Learning Tactics from Playing Videos

The aim of this research is to help players acquire skills for learning tactics from play videos. Our system gives a video that functions as a question and lets a player explain her tactics as an answer. It gives feedback if her answer's explanation does not satisfy the constraint of the actions with causal relations.

Fig. 1 shows the system configuration. The system consists of an interface that allows players to input explanations, a video database that stores the play videos of good scenes and their start and end situations, and an explanation-evaluation function. The interface gives players video of a play in which a certain objective was achieved and a description of its start and end situations. After receiving the player's explanation of the video, the explanation-evaluation function determines whether the actions of the input explanation have a cause-and-effect relation and gives feedback if there are actions without causal relationships. If the players selected action sequences that do have cause-and-effect relations, they successfully acquired a skill for learning tactics from a playing video.

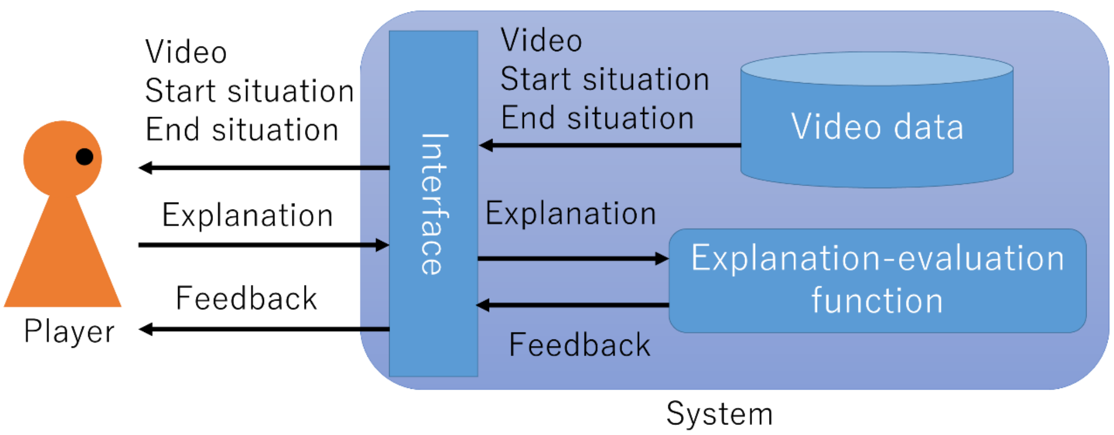


Fig. 1 System configuration

3. Format of Explanation

In e-sports, since the competition's situation is changed by player actions, a game is defined by sequences of situational elements and actions (Fig. 2). An explanation is a subset of the situational elements and actions that have cause-and-effect relations.

In the explanations, the reasons for selecting the actions must be described. As mentioned in Section 1, in actions with causal relations, situations derived by the former action lead to a latter action. Therefore, situational elements that are derived by the former actions and those that trigger the latter actions become the reasons for selecting them.

Our system lets players explain the given scenes by indicating actions that seem important, the situational elements that serve as the condition for taking an action (*action condition*), and the situational elements that are changed by the action (*action goal)*. For example, if "*move closer to the enemy*" action seems important in the video, "*the distance from the enemy is long*" action condition and "*the distance from the enemy is short*" action goal must also be input.

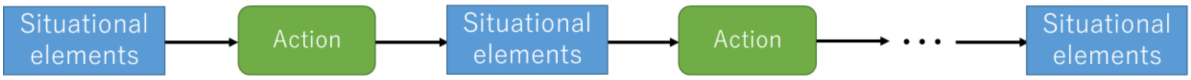
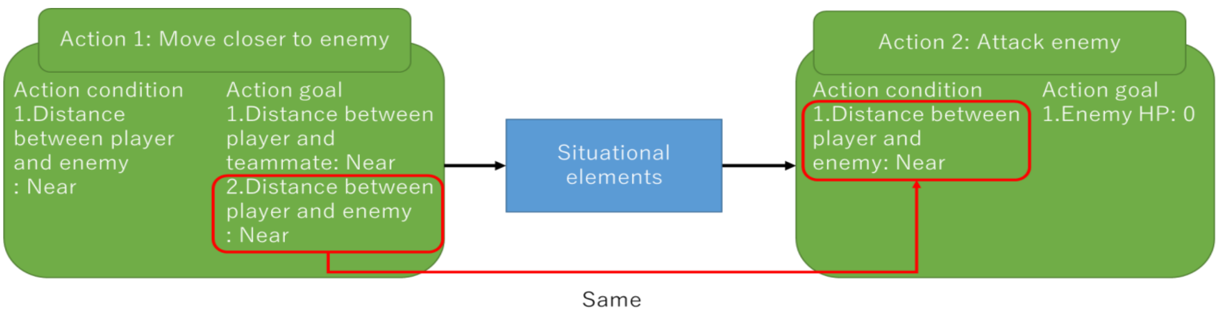


Fig. 2 Explanation format

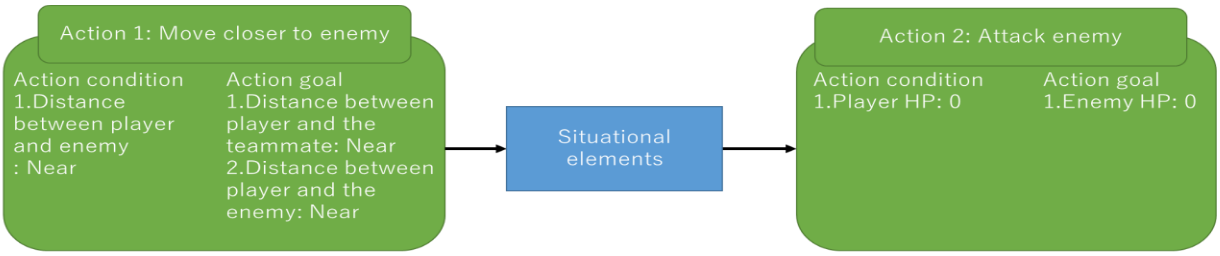
4. Explanation-Evaluation Function

The explanation-evaluation function determines whether the descriptions of the actions input by players have cause-and-effect relations. The action condition of the latter action and the action goal of the former action are used to evaluate whether a cause-and-effect relation exists between two actions. If the action condition of the latter action is included in the action goal of the former action, the two actions are defined as having a cause-and-effect relation.

Figure 3 shows examples of two actions. In Fig. 3a, since both the action goal of Action 1 and the action condition of Action 2 show "Distance between you and enemy: near," Action 2 is defined as the effect of Action 1. In Fig. 3b, since the action goal of Action 1 and the action condition of Action 2 do not have the same situational element, they have no cause-and-effect relation.



a) Actions with cause-and-effect relation



b) Actions with no cause-and-effect relation Fig. 3 Example of selected actions

The explanation-evaluation function checks the action goal of the former action and the action condition of the latter action for every pair of continuous actions and, if the situational elements are not identical, the player is led to find different actions that have cause-and-effect relations.

5. Prototype System

We implemented our proposed system in C#. Its main screen is shown in Fig. 4. The play video that the player must watch and explain is shown in the video area. The created explanation is shown in the explanation-display area. The videos were played on a Windows Media Player.

When the system begins, only the start and end situations of the play in the video are given in the explanation-display area. Therefore, the player needs to select actions that connect these given situations and input them into the system. This system provides two methods for creating explanations: adding a next action and its action goal for the given situation (*forward explanation*), and adding a former action and its action conditions for the given situation (*backward explanation*). When adding actions, the player needs to select a method from the explanation–method-selection area. After selecting it, the explanation-input screen emerges (Fig. 5). The player edits or deletes the created explanation by pushing the explanation-edit button to move to the edit-explanation screen whose contents are identical as the explanation-input screen. When the player finishes inputting her explanation and pushes the explanation-complete button, the system determines whether the actions in the created explanation are appropriate; if they are not, it gives feedback: e. g. “There is no cause-and-effect relation between Actions 1 and 2.”

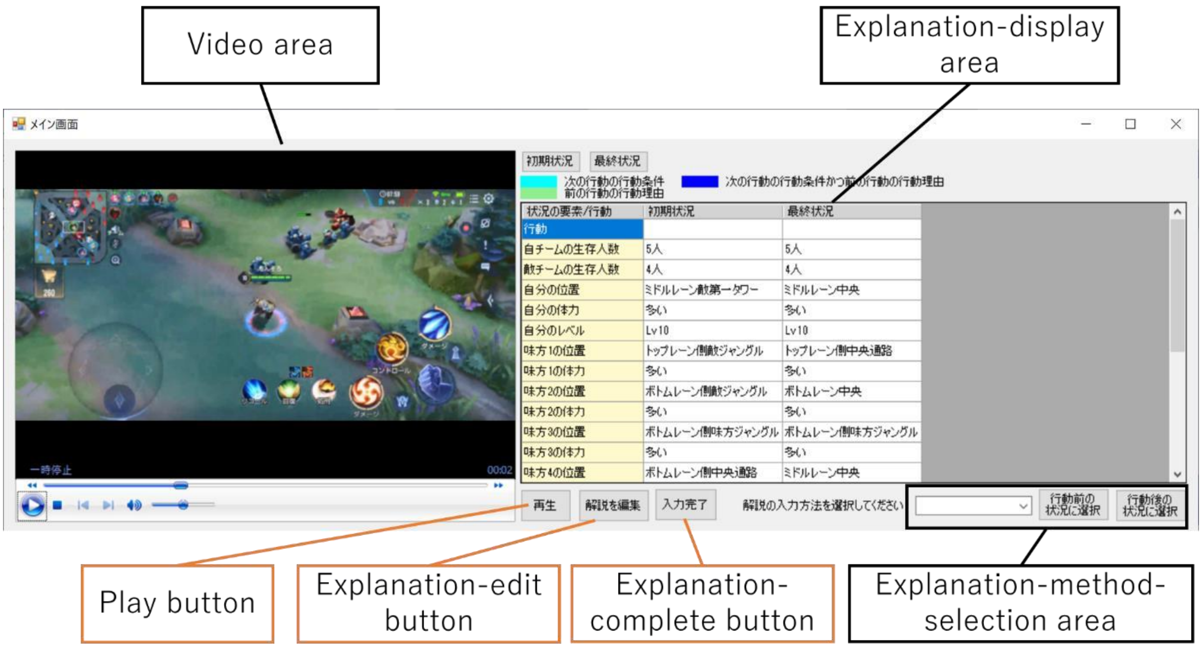


Fig. 4 Main screen

Figure 5 shows the explanation-input screen. Other than the explanation-input area, its layout is identical as the main screen. In the explanation-input area, the action, the action condition, the action goal, and the post-action situation can be input. To simplify the players' ability to grasp the situation, the system provides the elements of the situation and their values as candidates and lets one to be selected. The current system focuses on the MOBA game genre and provides the elements of the situation and their values (Table 1). In MOBA, multiple players are divided into two teams, and each player controls a character and cooperates with teammates to destroy the enemy towers. By inputting to the explanation-input area and pushing the add button, the input action and its next/former situations appear in the situation-display area.

Table 1 Elements and values of situations

Elements	Values
Character location	Enemy team's tower, player team's tower, jungle, etc.
Character HP	Big, half, small, zero
Character level	1 to 15
Number of towers	0 to 9
Tower HP	Big, half, small, zero
Field monster HP	Big, half, small, zero
Distance between characters	Long, short

Fig. 5 Explanation-input screen

6. Evaluation Experiments

6.1 Experimental settings

We experimentally evaluated the effectiveness of our system. As the first step for acquiring skill, the system only supports players to create explanations that satisfy the cause-and-effect relations. Therefore, the experiment evaluated how effectively the system support players to generate causally connected explanations, how well it support players to acquire tactics, and the interface's operability.

As playing video data, we prepared two videos of a MOBA game called "Arena of valor." The first 7-second video includes a "*move closer to an enemy to attack*" tactic, and the second is a 25-second video that includes the following complicated tactic: a "*defeat the field monster, move near the enemy, attack it, move near the field monster, and attack it.*" Unfortunately, our experiment only had five university students who had not played MOBA games and one university student who had played them several times as participants due to COVID-19 effects. They belonged to the computer science department and were recruited for this experiment.

First, our participants watched the videos and described the tactics used in them (Step 1). Next, they used the system to explain the scenes of the same videos (Step 2). Then, they described the tactics again (Step 3). Finally, they filled out a questionnaire (Step 4).

The questionnaire used in this experiment is shown in Table 2. Question 1 investigated whether using the system simplified the creation of the explanations, and participants answered on a 4-point scale: yes, somewhat yes, somewhat no, and no. If they answered somewhat no or no, they chose a reason from the following options: "interface is difficult to use," "important situations/actions are difficult to find," and "other." Question 2 asked about the operability of the interface, and participants answered on a 4-point scale: yes, somewhat yes, somewhat no, and no. If they answered somewhat no or no, they described the reason. Question 3 asked about the feedback's effectiveness, and those who received feedback from the system answered by selecting from "yes" or "no." If they answered "yes," they chose the reason from the following options: "I didn't understand the feedback," "I didn't know where to correct," or "other."

Table 2 Questionnaire items

Q1	Was it easy to create explanations using the system?
Q2	Was it easy to use the interface?
Q3	Was it difficult to modify the explanations based on the feedback?

6.2 Results

We evaluated the system's effectiveness for acquiring tactics by comparing the action sequences of the tactics described in Steps 1 and 3 with those of the expected tactics. Table 3 shows the results. Participant *F* of Video 1 and participants *A* and *B* of Video 2 were unable to extract the appropriate action sequences in Step 1, although they did extract the appropriate one in Step 3. Participant *F* extracted the "gain experience" action in Step 1 in Video 1. By using the system in Step 2, he realized that the action was irrelevant to the tactic and removed it, suggesting that the system contributed to the acquisition of tactics. On the other hand, participants *D* and *E* of Video 2, who could not extract the assumed action sequence in either Steps 1 or 3, also failed to extract the "move toward the field monster" action. In Step 2, they input the "move toward the field monster" action to the system as an explanation, although they did not appropriately describe the situational elements for finding the cause-and-effect relations. Had they appropriately observed the situational change, they probably would have extracted an appropriate action sequence as a tactic.

We evaluated how effectively the system support participants to generate causally-connected explanations based on whether they were generated in Step 2 and in the Q1 and Q3 results. Table 4 shows the results about whether the explanations with causal relationships were made in Step 2, and Table 5 shows the questionnaire results. From Table 4, no one created an explanation with cause-and effect action sequences in Video 2, although participants *C* and *E* created explanations with cause-and effect action sequences in Video 1. Participant *E* initially failed to create an appropriate explanation. Based on the system's feedback, he modified his explanation and successfully created an appropriate one. Unfortunately, for the other cases, the system's feedback did not improve the explanations. From the Q1 result in Table 5, participants *A*, *B*, and *E* answered "somewhat no" to the ease of creating explanations. In addition, the Q3 result shows that five out of six participants answered “yes” to the difficulty of revising the explanation through the system’s feedback. The difficulty reflected that the system only indicates two actions that do not have a cause-and-effect relation, and so participants did not understand why the indicated actions were inappropriate. These results show that the system’s feedback was insufficient to help participants create appropriate explanations.

We evaluated the interface’s operability by the Q2 result, which shows that half of the participants answered “somewhat yes,” and the other half answered “somewhat no” about the ease of using the interface. In addition, many participants answered that inputting the situations and actions into the system was difficult. This result shows that our system’s interface is not very user friendly and it must be improved for entering situations and actions.

Table 3 Are extracted action sequences identical as expected action sequences?

Participants	Video 1		Video 2	
	Step 1	Step 3	Step 1	Step 3
A	Y	Y	N	Y
B	Y	Y	N	Y
C	Y	Y	Y	Y
D	Y	Y	N	N
E	Y	Y	N	N
F	N	Y	Y	Y

Table 4 Were appropriate explanations made with system? (in Step 2)

Participants	Video 1	Video2
A	N	N
B	N	N
C	Y	N
D	N	N
E	Y	N
F	N	N

Table 5 Questionnaire results

Cooperators	Q1	Q2	Q3
A	Somewhat no	Somewhat no	Yes
B	Somewhat no	Somewhat yes	Yes
C	Somewhat yes	Somewhat no	No
D	Yes	Somewhat yes	Yes
E	Somewhat no	Somewhat yes	Yes
F	Somewhat yes	Somewhat no	Yes

7. Conclusion

We proposed a method that acquired tactics from the play videos of skilled players by choosing action sequences that have cause-and-effect relations as explanations. We also developed a system that supports players who create explanations for the given videos as the first step for developing skills for finding actions that form tactics. The system gives feedback when the selected action sequences lack cause-and-effect relations. Our evaluation experiment suggests that players derived tactics after using the system, although its feedback did not help them create explanations with the actions of cause-and effect relations. Unfortunately, we haven’t yet evaluated our system in the context of acquiring skills for finding effective actions. We need further experiments to evaluate how the system contributes to support acquiring skill.

Our method for supporting players to identify and acquire tactics from the playing videos of skilled players is appropriate for tactics that have only one cause-and-effect relation path. However, there are usually tactics whose actions have several causes and who affect to several actions. We need to improve our system to cope with such tactics.

In addition, our method can apply to tactics that can improve situations, since it is easier to choose good actions. However, other tactics can be used to avoid worsening game situations and maintain the current situation. Such tactics are difficult to acquire by observing play videos. To grasp them, players need to anticipate the future situation based on the current situation. If the anticipated situation is worse but the play video does not get to that worse situation, players will notice the tactics for maintaining the current situation. So we should introduce to our method the phases that anticipate future situations and compare anticipated situations and those in the video.

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