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Tactical Knowledge Acquisition Support System from Play Videos of Esports Experts

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Abstract: Esports are a competition that involves computer games and video games that are played online. Some expert players upload videos of their play (play video) on the internet. In esports, understanding various tactical knowledge is important so that players can take appropriate actions based on such situations. Unfortunately, players have inadequate opportunity to learn them. The video performances of experts who play esports contain scenes where various tactical knowledge has been adopted by the experts. The objective of our research is to support players' grasping about the tactical knowledge of experts from their play videos. This research provides a system that extracts such components of tactical knowledge as sequence of actions, applicable situations, and its effects from good scenes that are selected by players from the play videos.

Keywords: computer game, observational learning, play videos, tactics acquisition

1. Introduction

Esports, which is an abbreviation of "electric sports," denotes competitions of computer games and video games. They are originated in a small competition at Stanford University in the United States in 1972. Their play popularity continues to rise as well as the numbers of people who engage in them (Jenny et al., 2017). Various types of games are provided as esports, and the skills required to play them are based on particular games. However, in all esports, players need to choose actions and strategies and exploit decision-making abilities to take appropriate actions that react to a competition's situation. This is the same as physical sports. That is, a soccer requires the skills of kicking the ball and a tennis requires the skills of hitting the ball, but decision-making abilities are just as important for both competitions.

Baker et al. argued that since decision-making abilities in physical sports such as soccer and tennis are implicit and gained through experience (Baker et al., 2003), few effective training methods have been established. In physical sports, players usually learn the appropriate actions for each situation from constant feedback and comments from coaches, managers, and teammates when reflecting their play. Unfortunately, players who do not share the same physical space with such experts lack opportunities to be given comments.

To compensate for the absence of experts and provide an opportunity to learn from them, Zhai et al. created an online coaching-support system for esports (Zhai et al., 2005). In esports, plays are easily recorded as videos (play video) and are shared through the Internet. In the system of Zhai et al., an expert and players in a distributed environment can interact and exchange annotated snapshots extracted from play videos. Based on annotations, the scenes where coaches provide comments can be grasped. However, since the quality of the comments differs based on the coaches, players are not always able to understand which actions are appropriate.

Some systems foster decision-making skills. Takahashi et al. proposed a training system for decision-making in disasters (Takahashi et al., 2017). Their system contained branched-training scenarios that are created to cope with unexpected situations during a disaster and simulates them with VR images. At branch points, users need to make decisions whose results are provided as selected scenes. Since the knowledge that should be acquired in a disaster can be assumed in advance, scenarios can be prepared. However, in esports with a short history, since the target decisions to learn are not clear, creating scenarios is difficult. For making appropriate decisions, understanding effective actions as tactical knowledge and applying them based on the situation are important.

In the field of physical sports, some systems provide analytical tools to grasp the tactical knowledge (Saito et al., 2015, Wu et al., 2017). These systems only provide the analysis tools, such as to derive the characteristics of winning games, but the way of interpreting the results is not supported. Thus, players without analytical skills cannot acquire tactical knowledge by themselves. In order to support players to acquire tactical knowledge independently, the system needs to extract tactical knowledge automatically.

Some systems disseminate tactical knowledge by giving feedback about players' actions (Vales-Alonso et al., 2015, Janusz et al., 2018). Feedback emphasizes inappropriate actions and suggests alternative strategies. Both of these research only suggest appropriate actions to the current situation without indicating the appropriate situations in which to apply them. Therefore, players struggle to apply the actions to other situations. The effect of applying the suggested actions is also unclear.

The objective of this research is to support players who want to acquire tactical knowledge that consists of a sequence of actions, the situations in which to apply it, and its effect. The moves of players are regarded as scenes in which tactical knowledge is being applied. Novice players must grasp the tactical knowledge from the plays and decisions of other players, especially from better, more experienced players. In esports, videos of the games played by good players can be easily obtained through the Internet. This research develops a tactical knowledge acquisition support system that extracts such components of tactical knowledge as sequences of actions, situations in which to apply them, and their effects from scenes selected by players from play videos.

2. Overview of Tactical Knowledge Acquisition Support System

2.1 Decision Making in Esports

In ball games such as tennis and soccer, in which the ball is used as an intermediary to alternately interfere with the opponent and compete directly, Nakagawa defined decision making as "making a decision about the play to be performed in the game" and argued that it consists of the four steps shown in Figure 1 (Nakagawa, 1984). The decision-making process in esports takes these four steps.

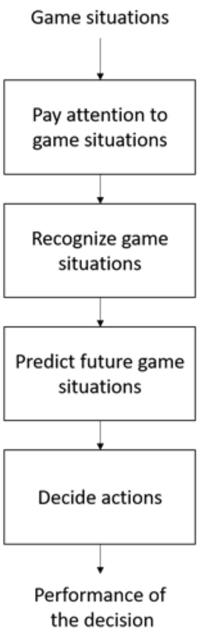

Figure 1. Decision-making Process in Ball Games (Nakagawa, 1984).

In the “pay attention to game situations,” players concentrate on the appropriate elements of the perceived situation. In “recognize game situations,” they evaluate the perceived elements to react to the current game situation. “Predict future game situations” infers the future game situations based on recognized current game situations and action candidates. Since possible future situations differ depending on the candidates of the sequence of actions, various situations can be inferred. In “decide actions,” players determine potential strategies based on those that the player can exploit to her advantage. To select an effective action for a situation, future situations need to be weighed at the “predict future game situations.” Since future situations are derived by applying applicable actions to the situation, recognizing applicable actions from the situation is important. This paper defines the possible actions from each situation as tactical knowledge and helps players acquire such knowledge.

2.2 Tactical Knowledge Acquisition Support System

This paper defines tactical knowledge consists of a sequence of actions, situations where those actions can be applied, and their effects. For example, in baseball, when the out count is 0 and the player hits a fly ball to the outfield, the runner on the third base runs to the home base. In this tactical knowledge of the runner, a sequence of actions is “run and touch the home base”, and the situation of applying this tactical knowledge is “out count is 0 and the player hits a fly ball.” Its effect is “to gets 1 point.”

Players apply tactical knowledge during games. Play videos indicate scenes where such knowledge is applied and the application results. Therefore, a tactical knowledge acquisition support system encourages the comprehension of such knowledge from the play videos of experts.

If tactical knowledge is effective, a player’s situation becomes more advantageous than her opponent. Therefore, the sequence of actions that changes her situation in her favor is regarded as effective tactical knowledge for her. For example, in fighting games, if a player successfully decreased the life (HP gauge) of her opponent, her actions are labeled as successful tactical knowledge for that action that decreased the HP gauge.

Applying actions is one situation where tactical knowledge can work well and improve a player’s outcome. However, a situation is comprised of various elements, all of which are not always necessary for applying tactical knowledge. Some elements are relevant to the application of tactical knowledge; some are not. Relevant elements may commonly be recognized in scenes where identical tactical knowledge is applied. Our system provides an environment that allows users to cut out scenes from play videos to support their acquisition of tactical knowledge by presenting actions, situations, and effects from the common points of the extracted scenes.

Figure 2 shows an overview of our system. The interface shows the play videos and provides functions for extracting scenes deemed useful by users. For supporting the selection of scenes, the interface provides a time chart that shows the changes of the elements of the situations and the actions of the players who changed them. Annotations are attached to the extracted scenes that represent good types that are stored as candidates of tactical scenes. Annotations can be freely attached by users, for example, “a scene that decreases my opponent’s HP gauge” or “a scene that forces my opponent to another room.”

The interface for extracting tactical knowledge helps users acquire it from the extracted scenes. A list of the annotations of extracted scenes is presented. Based on the selection of annotations by users, a function, which extracts tactical knowledge, extracts sequences of meaningful actions and meaningful elements of the start situations of the scenes with identical annotations as the tactical knowledge in scenes.

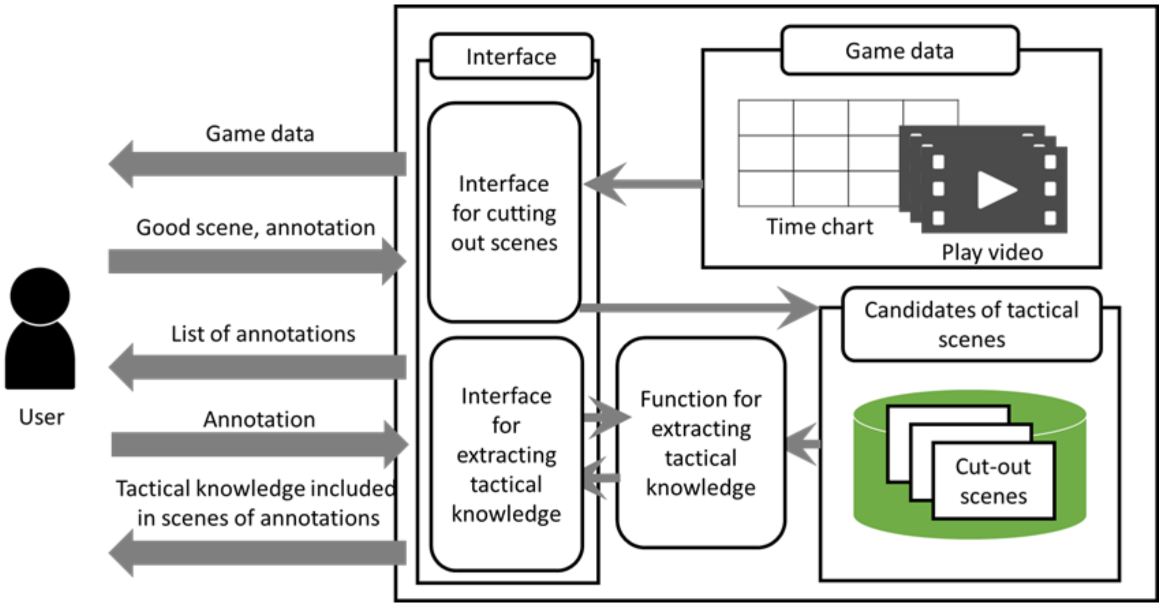

Figure 2. System Overview.

3. Data Representation

3.1 Time Chart

A time chart expresses the game's progress by the actions taken in one time step and the change of the situation's elements based on such actions.

As an example, Table 1 shows part of the time chart for a fighting game, called Street Fighter V. In this game, there are two characters: the one operated by the player who is making the video and his opponent. They attack each other until either of them loses his life or the time is up. The first two lines show the actions for each time step. Since both players usually take actions simultaneously, the actions of two characters are written on one row. From the third line, states are shown. Their states are represented by the position, the remaining life (HP gauge), the power to use the strong attacks (EX gauge), and the power to use the special technique (V gauge). The position is set in either the field or near a wall. An HP gauge is represented by four values: high, medium, low, and minimal. EX and V gauges are expressed by 0, 1, 2, and 3. The state of the game space shows the positional relations between two characters and the remaining time. The positional relation is represented by three values: far, near, and close. The remaining time is represented as much or little.

Currently the time charts are prepared manually by authors. To create them automatically by analyzing the play videos remains as future work.

Table 1. *Part of Time Chart for Street Fighter V*

Action	Player's character		Kick	Fire ball	Fire ball	Fire ball
	Opponent's character		Defend	Bending backward	Defend	Fire ball
State	Player's character	Position	Field	Field	Field	Field
		HP gauge	High	High	High	High
		EX gauge	2	2	2	2
		V gauge	2	2	2	2
	Opponent's character	Position	Field	Field	Field	Field
		HP gauge	Low	Low	Low	Low
		EX gauge	1	1	1	1
		V gauge	2	2	2	2

Game space	Positional relation of two characters	Close	Close	Far	Far
	Remaining time	Much	Much	Much	Much

3.2 Tactical Scene

Tactical scenes are stored by scene data and annotations are attached by users. Scene data consist of five elements: the actions of the player's character, the actions of the opponent's character, the start situation, the end situation, and effects that consist of differences between the start and end situations. The player and opponent actions are the sequence of actions from the start to the end of the scenes. The situation consists of the values of each state element. These four elements are automatically generated based on the time chart when the scene was extracted by the user.

4. Function for Extracting Tactical Knowledge

The function that extracts tactical knowledge, such as meaningful actions, the elements of situations, and effects, from candidates of tactical scenes of identical annotation.

The meaningful start situations are the common elements of the start situations, and the meaningful end situations are the common elements of the end situations of the candidates of tactical scenes of identical annotation. The effect is the difference between the meaningful start and end situations. Table 2 shows example of start situations of tactical scenes 1 and 2. In this case, the meaningful elements are: Player.Position=Field, Opponent.Position=Field, Opponent.HP=Low, Opponent.EX=1, Game space.Remaining time=Much.

Table 2. *Example of Start Situations of Tactical Scene 1 and 2*

State		Tactical scene 1	Tactical scene 2
Player's character	Position	Field	Field
	HP gauge	High	Medium
	EX gauge	3	1
	V gauge	3	2
Opponent's character	Position	Field	Field
	HP gauge	Low	Low
	EX gauge	1	1
	V gauge	2	3
Game space	Positional relation of two characters	Close	Far
	Remaining time	Much	Much

On the other hand, a meaningful sequence of actions is also a common sequence of the actions of the candidates of tactical scenes. Since various sequences of actions can cause the same effect, the candidates of tactical scenes should be classified into groups to derive the common sequences of actions within groups. To classify the candidates of tactical scenes, the similarity between action sequences must be calculated. In this study, we applied the Levenshtein distance and defined the number of operations to make one action sequence to the other as a similarity. Here the operation is comprised of insert, delete, or replace. For example, in Figure 3, since one action is deleted from sequence 1 to become sequence 2, their similarity is 1. Tactical scenes whose similarity is small are classified as one group.

However, since time charts have every action for each time step, not all actions are important. For example, assume that throwing fire balls after kicking is critical tactical knowledge, and a small movement before throwing the fire balls does not affect the tactical knowledge. In this case, adding or deleting the movement action between a kick and a fire ball is meaningless. Since such meaningless operations do not affect the calculation of similarity, this study assigns their values as 0 for calculating similarity.

Meaningless operations differ based on the game. For example, Street Fighter V has nine action categories: punch, kick, throw, launching a projectile, counter, special move, defensive move, movement, and jump. The following are regarded as meaningless operations:

1. inserting/deleting/replacing a movement action;
2. replacing actions of the same category;
3. inserting/deleting actions of the same category for both sequences.

According to this definition, the similarity of action sequences in Fig. 3 is 0, since the value of deleting the movement action is 0.

By calculating the similarity, the candidates of tactical scenes whose similarity is zero form one group and the action's minimal sequence is regarded as the action sequence of the tactical knowledge.

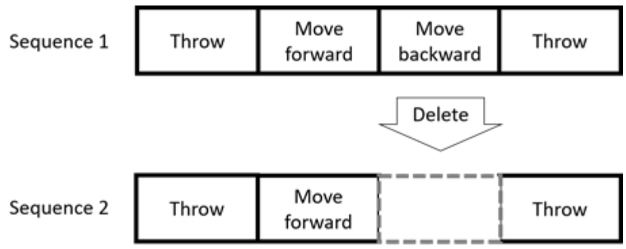

Figure 3. Example of Action Sequences.

5. Prototype System

We implemented our tactical knowledge acquisition support system in C # programming language. In this system, a user has only two main operations to view the tactical knowledge. The first is to cut out some scenes that they think are good for games. The second is to select what a user wants to view from the tactical knowledge automatically extracted by the system.

When it starts, a home screen appears that consists of two tabs. When a user selects a play video from the list and presses the OK button, she moves to the interface for extracting scenes. When she presses the tactical knowledge extraction button, she moves to the interface to extract tactical knowledge.

Figure 4 shows the interface for cutting scenes. A selected play video is shown in the displaying play video area and its time chart is shown on the displaying time chart area. When a user clicks on a certain point in the area for displaying time charts, the play video's seek bar moves to the corresponding scene, where the user can watch it. The user presses the mode change button to shift to the scene cutout mode from the play video watching mode. Here the user can extract scenes by selecting the start and end scenes and pushing the decision button. The sequence of actions in the cut-out scene is displayed in a list that displays action sequences. The left side of the action sequence list is a combination box for annotations, where the user can attach them to cut-out scenes. When the user presses the mode changing button again, the scene cutout mode ends, and the mode returns to the play video watching mode. By pushing the save button, the system stores the extracted scenes in an XML format.

Figure 5 shows the interface for extracting tactical knowledge. When a user selects from a list of annotations, a list of action sequences of the tactical scenes of the selected annotations is displayed in the list of the action sequences among all the tactical scenes. When a user selects from the list of meaningless operations, the similarity is calculated based on the selection methods, and meaningful actions are shown in the list of meaningful action sequences. If a user selects a meaningful action sequence, its start situations and effects are displayed in the displaying tactical knowledge area.

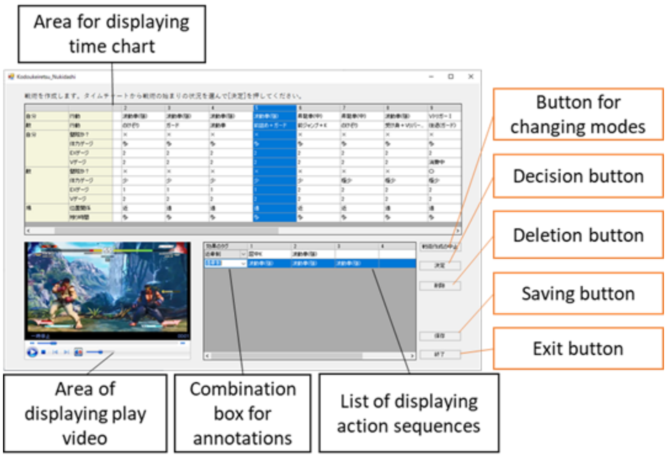

Figure 4. Interface for Cutting out Scenes.

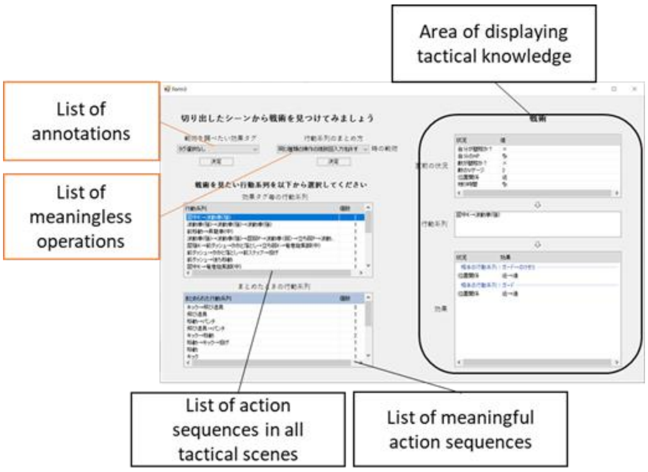

Figure 5. Interface for Extracting Tactical Knowledge.

6. Evaluation Experiment

6.1 Outline

We experimentally evaluated the effectiveness of our tactical knowledge acquisition support system that obtains tactical knowledge. We prepared three play videos from Street Fighter II where the same expert used the same characters. Our research participants were 13 beginners to the Street Fighter series.

In the research, the participants watched the play video, grasped the tactical knowledge exploited by the expert, and wrote it down (Step 1). Next they used the interface to extract those scenes that they felt were good and described any tactical knowledge that they learned (Step 2). After that, they used the interface to extract tactical knowledge by browsing through the situations, actions, and effects from the cut-out scenes and added a description of new tactical knowledge that they learned (Step 3). Finally, they answered questions (Step 4).

We evaluated our system's effectiveness in terms of the comprehension of tactical knowledge and its quality. We evaluated such example of comprehension by comparing the amount of tactical knowledge described in Steps 1, 2, and 3. Regarding the quality of the tactical knowledge, grasping every element is preferred, such as action sequences, situations, and effects. Various elements of the situation must also be recognized. Therefore, evaluations are based on the amount of tactical knowledge described by situations, effects, and the number of elements in the situation.

Table 3 shows the questions asked in Step 4. Participants selected one answer from "yes," "for the most part, yes," "for the most part, no," and "no." Question 1 asks about the interface's effectiveness for extracting scenes, and question 2 asks about its extraction of tactical knowledge.

Table 3. *Question Items*

ID	Questions
1	Was extracting the scenes easy?
2	Did the displayed sequence of actions, situations, and effects help you grasp tactics?

6.2 Experimental Results

Table 4 shows the amount of tactical knowledge each participant learned and wrote down in Steps 1, 2, and 3. Table 5 shows the answers of questions. All participants acquired new tactical knowledge in Step 3. In addition, the total number of descriptions in Steps 2 and 3 were more than double the number of descriptions in Step 1 for ten participants. The correlation coefficient was 0.422 between the number of cut-out scenes and the descriptions in Steps 2 and 3. A positive correlation was found between the number of cut-out scenes and the amount of described tactical knowledge. These results indicate that our system was effective for acquiring new tactical knowledge.

For the effects of individual interfaces, some participants noted more descriptions in Step 3 than in Step 2; some noted more in Step 2. In the answers to questions 1 and 2 in Table 5, almost all participants chose "yes" or "for the most part, yes." Based on these results, both interfaces support the acquisition of new tactical knowledge.

Table 4. *Amount of New Tactical Knowledge*

Participant	A	B	C	D	E	F	G	H	I	J	K	L	M
Step 1	8	9	11	6	4	3	4	5	3	4	7	3	8
Step 2	4	5	0	6	0	0	3	3	4	2	1	2	2
Step 3	4	5	6	2	5	3	1	4	3	2	5	2	3

Table 5. *Answers of Questions (Number of People)*

ID	Yes	For the most part, yes	For the most part, no	No
1	5	7	1	0
2	8	5	0	0

We evaluated the quality changes of the tactical knowledge after using the system. Table 6 shows the number of elements described in the situation and the effect elements. Participants C, E, F, G, and K described both the situation and the effect after using the system, and nine of them increased the number of elements to focus on. Participant H just wrote down one action: "making a combination moves with a small movement and then hit with a big movement" before using the system as one piece tactical knowledge. After using this system, he described the situation and the effect: "when the opponent was not against the wall, push her to the wall to skillfully cause large damage." On the other hand, participant I who did not see any change after using the system said, "To learn the tactical knowledge with the system was slightly difficult because this was the first time that I watched this game." These results suggest that this system more effectively improved the quality of tactical knowledge for users who already had a rudimentary knowledge of the game.

Table 6. *Number of Elements of Situation and Effect Described in Tactic Knowledge*

Participant	A	B	C	D	E	F	G	H	I	J	K	L	M
a) Situation													

Step 1	3	1	2	1	0	1	2	2	2	4	3	0	2
Steps 2 and 3	4	1	2	1	2	3	2	3	3	4	3	0	2
b) Effect													
Step 1	1	0	0	0	1	0	0	1	0	2	0	0	2
Steps 2 and 3	2	0	1	0	3	1	1	4	0	3	1	0	2

7. Conclusions

We constructed a system that extracts the elements of tactical knowledge from an expert's play video scenes selected by users to support the acquisition of tactical knowledge. Based on our experimental results, using the system increased the amount and improved the quality of the tactical knowledge understood by our participants. This result suggests that extracting scenes and deriving common points from them were effective for acquiring new tactical knowledge.

This system extracts situations and effects that are common to the all tactical scenes of identical annotation. Tactical knowledge can be applied to various situations. If such knowledge does not appear as common features in the extracted play videos, this system cannot extract it. Although such features might not appear in all of the tactical scenes, they do appear in most of them. To extract the common features that appeared in many tactical scenes, a function must be created that extracts the elements in the situations and the effects seen in more than a certain number of tactical scenes.

In addition, the current system regards the common elements of situations and effects as meaningful aspects. However, not all of them are relevant to tactical knowledge. We need to investigate the important elements by interviewing experts and analyzing the relationships between each element and the game flow to create a function that only extracts meaningful elements as tactical knowledge.

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