# Observer Interface Focused on Trends of Character Movement and Stamina in Fighting Games

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***Abstract*—This paper proposes an observer interface that focuses on the trends of character movement and stamina in fighting games. A fighting game is a genre of e-Sports in which two players fight each other by controlling a character that imitates a fighter. A previous observer interface provides observer support, which considers the positional relationship between characters on the game screen. In contrast, this paper proposes an observer interface that focuses on the distance that the character moves, the frequency of this movement, and the reduction in the character's stamina, while also visualizing the wider trends in movement and advantage within a specific period of time.**

***Index Terms*—e-Sports, fighting game, supporting spectators, user interface, information visualization**

## I. Introduction

This paper proposes an observer interface that focuses on the trends of character movement and stamina in fighting games. A fighting game is a genre of e-Sports [1] in which two players fight each other by controlling a character that imitates a fighter. While the theoretical shape of the game field can be 2D or 3D, this paper focuses on 2D game titles. Previous research on fighting games includes studies focused on developers rather than players, such as research on character AI operated by the computer [3] and research on judgements related to long "combos [5]." On the other hand, in terms of research designed to support players who are also observers, game play analysis using the player's gaze [4] and observations based on the position of the character on the screen has also been conducted [2]. This paper, however, focuses on the observers. The previous observer interface provides observer support, which considers the positional relationship between characters on the game screen. In contrast, this paper proposes an observer interface that focuses on the distance that the character moves, the frequency of this movement, and the reduction in the character's stamina, while also visualizing the wider trends in movement and advantage within a specific period of time.

## II. Proposed Method

### A. Concept

In a fighting game, the focus tends to be on ' showy ' techniques and powerful combos. However, skilled players who participate in e-Sports competitions are excellent at applying a steady stream of simple moves and attacks. To the untrained eye, these simple moves and attacks are difficult to understand simply by observing them. This paper solves this problem by visualizing the trends in movements and advantage of a character. There are other parameters reflecting character's features and player's skills, are not visualized on the standard general fighting game interface, other than the trends in movements and advantage of a character. There are two reasons for focusing to the trends in movements and advantage of a character in this paper. One of reason is that the trends in movements and advantage of a character are associated with good/not good tactics of character selected by players. In a fighting fighting game, character's positioning on the game field is important, and it is more advantageous for the character to attack well and drive an enemy character to the corner of the game field. Second reason is that we had comments that desiring to know the trends in movements and the situations in which the a character attacks enemy character intermittently obtained from three casual players (spectators).

Trends in movement refers to the distance that each character has moved to the left or right during the fight (move distance), as well as how many times they have moved in either direction (number of movements). Advantage compares the amount of damage received by each character within a certain period of time, with the character that has inflicted the largest amount of damage to its opponent within a certain period of time being the dominant character.

According to the method proposed in this paper, in order to calculate both the move distance and the number of movements, the position of the character in the game field must be extracted from the game play, and likewise, to determine whether a character is dominant, the extent to which the character's stamina has been reduced must also be extracted. Therefore, in this paper, through template matching using the image processing library OpenCV, both the character's position and the extent to which the character's stamina has been reduced were first been extracted from the game play and then visualized. In this paper, the proposed interface has been implemented on "Street Fighter V," while the video resolution discussed is $1280 \times 720$ pixels. This paper explains the example of the proposed method and the proposed interface using

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figures created by the authors, in consideration of the copyright of the game images.

Implementation methods described in this paper does not modify the game software program. Visualization of the trends in movements and advantage of a character realized by this paper is preferably included in the game software in the actual application.

### *B. Extracting the Situation from the Game Movie Through Template Matching*

The template matching method for extracting the position$x_t^n$ of the character $n$ at time $t$, as well as the position $x_t^m$ of the character $m$ at time $t$ (see Fig. 1, $n$ is one character and $m$ is another character), adopted the method used in previous research [2]. The template image was obtained by trimming using rectangular areas with colors that are characteristic to the characters. Template matching was performed for every frame (1/30 seconds).

Next is the explanation of template matching for the stamina bar. The red and blue sections in Fig. 2 are template images for the stamina bar. A portion of the amount of damage already received by the character (red frame) and a portion of the amount of damage received immediately before the present time (blue frame) were each cropped to $14 \times 20$ pixels and generated at this size. The size of the template image was set based on the length of the stamina bar, which decreases with each low-power attack. Template matching was performed every 150 frames (5 seconds).

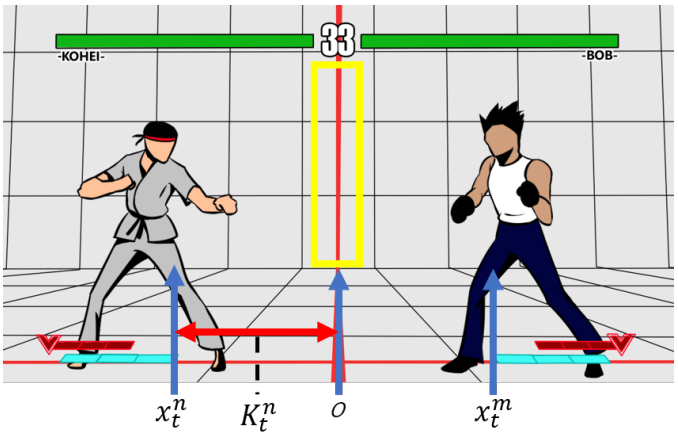


Fig. 1. A characteristic area in the center of the game field.


Fig. 2. Template image of the stamina bar.

### *C. Calculation and Visualization of Move Distance and Number of Moves*

The move distance of a character was obtained for each movement by the character in either direction. The accumulated distance in each direction is defined as the move distance. The amount of movement was calculated by determining the reference point $o$, obtaining the distance between the reference point and the position of the character (the positive/negative move direction to the left and right is also considered), and taking the difference from the distance 30 frames before. The reference point is a characteristic area in the center of the background of the game field, and the position was extracted through template matching. The area indicated by the yellow frame in Fig. 1 represents the characteristic area. Because the width of the game field is wider than the screen, depending on the position of the camera that follows the position of the character, the characteristic point is not at the center of the screen, but to the left or right. Equation (1) define the distance $K_t^n$ of any character $n$ from the reference point at time $t$. The position of $x = 0$ on the game screen is on the left edge of the game screen.

$$K_t^n = x_t^n - o \tag{1}$$

Where $x_t^n$ is the position of character $n$ at time $t$, the move distance is calculated based on the distance $K_t^n$ obtained using equation (1). Equation (2) defines the movement amount $\delta t$ of any character $n$.

$$\delta t = |K_t^n - K_{(t-30)}^n| \tag{2}$$

Here, $K_{(t-30)}^n$ is the distance between the character $n$ and the reference point at time $t - 30$. This determines whether each character moved forward/backward, taking into account the change in the character's positional relationship, as shown in Fig. 3. Here, forward refers to the character moving toward the opponent character, while backward refers to moving away from the opponent character. In Fig. 3, Cha1 is the position of character 1 and Cha2 is the position of character 2. As an example, the following is an explanation from the perspective of character 1. In case A, there is no change in the character's positional relationship from 30 frames before; therefore, if the value of $K_t^n$ is larger than $K_{(t-30)}^n$, the character has moved forward, while if it is smaller, the character has moved backward. In case B, the character's positional relationship is reversed compared with the previous 30 frames, and it is thus assumed that the character has advanced for 30 frames and does not assume that the character moved backward in the middle of those 30 frames.

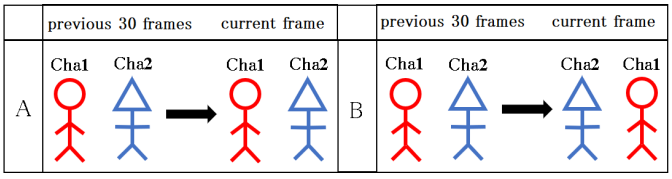


Fig. 3. Change in the positional relationship of the characters.

The amount of movement obtained using Equation (2) was accumulated separately for forward and backward movements, and was visualized in the form of a bar (hereafter referred to as the "move distance bar." An example of the visualization is shown in Section III). For visualization, the reference point of the move distance bar was set below the stamina bar at a position 2/5 of the length of the stamina bar when viewed from the edge of the screen. It then stretches to the left or right, depending on whether the character moves forward or backward. In a fighting game, it is assumed that the forward bar will be longer than the backward bar, since the move distance per a single operation on the controller is longer for the forward movement than the backward. When the character moves forward, the blue bar extends from the reference point toward the center of the screen. When the character moves backward, the red bar extends from the reference point to the edge of the screen. The number of moves is the number of times each character moves forward and backward every 30 frames (1 second), while the numerical values for the forward/backward movements are shown below the move distance bar.

### *D. Calculation of Reduction in Stamina and Visualization of Advantage*

The extent to which stamina has been reduced refers to the amount of damage each character has been dealt by the opponent character from the start of the game to any time $t$. This was calculated by the total number of red and blue frames obtained by template matching, as described in section II-A. If the number of red frames obtained through template matching is $a$ and the number of blue frames is $b$, the amount of damage $D_t^n$ to any character $n$ at time $t$ is defined by Equation (3).

$$D_t^n = a + b \tag{3}$$

In the proposed method, the stamina reduction amount was calculated every 150 frames (5 seconds) in order to visualize advantage within a certain time. Equation (4) defines the amount $L_t^n$ of stamina reduction at time t for any character n in 150-frame intervals based on Equation (3).

$$L_t^n = D_t^n - D_{(t-150)}^n \tag{4}$$

Based on the stamina reduction $L_t^n$ obtained in Equation 5, the reduction amount of both characters were compared, and character n with the smaller amount was determined to be dominant. In the visualization, the annotation "advancing" (hereinafter referred to as "advantage annotation") is displayed above the head near the position $x_t^n$ of character $n$ at any time t (specific examples are shown in Section III). It was visualized in the 60 frames (2 seconds) after advantage had been determined. Additionally, as a result of this determination, if the reduction amounts for both characters are equal, the advantage annotation was not shown.

## III. Observer Interface

Figure 4 is an example of the proposed interface. The move distance bar, the number of movements, and the advantage annotation are displayed on the screen. In the figure, the rectangle enclosed by the blue frame represents the move distance bar and the number of movements. In the figure, the rectangle enclosed by the red frame is the dominance annotation.

Figure 5 is an enlarged view of both the visualized move distance bar and the number of movements. The blue part of the bar is the distance moved forward and the red part is the distance moved backward. As for the numbers below the move distance bar, the blue numbers are the number of forward moves and the red numbers are the number of backward moves. Figure 5 shows that the distance the character has advanced is more than twice as long as the distance it has retreated. On the other hand, looking closely at the number of movements, there is not much difference between forward and backward movements, and it can thus be inferred that backward movements are repeated gradually. We can see the tendency of the character to move forward/backward based on the move distance bar, as well as the number of movements.

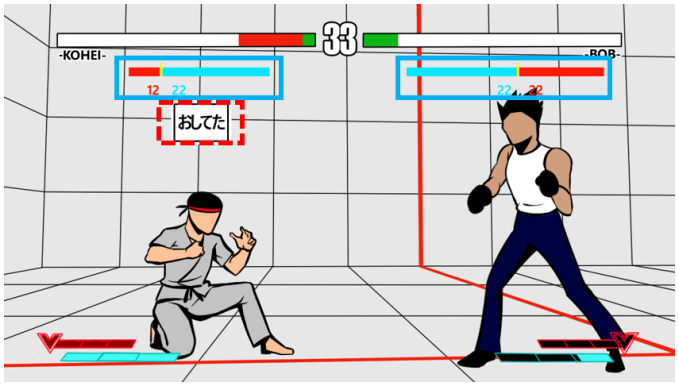


Fig. 4. Example of proposed interface.

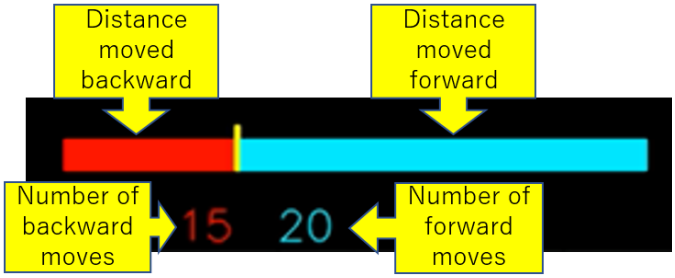


Fig. 5. Move distance bar and number of movements.

## IV. Preliminary Experiment on the Validity of the Advantage Annotation

The purpose of this experiment was to confirm the validity of the advantage annotation. In this experiment, the subjects were asked to watch 20 videos (consisting of 4 games) of game

play that were separated into 5-second clips. The subjects were three people (P1-P3) who play the fighting game on a regular basis. The procedure was as follows.

1) Ask the subject to watch the videos that are separated into 5-second clips.
2) Ask the subject which character was advantageous.
3) Move on to the next game and start from 1. After watching the 20 video clips, go to step (4).
4) Determine advantage of the videos in the experiment using the proposed interface and examine the consistency with the subject's determination.

Table I shows the result of the preliminary experiment. The number of matches in Table I indicates the number of responses from the subject that matched the result using the proposed interface. The ave. is the average score of the consistency rate for the three subjects. Table I shows that the consistency rate for all subjects was 68%, indicating that there is some validity.

TABLE I
PRELIMINARY EXPERIMENT RESULTS

| Subject | P1 | P2 | P3 | Ave. |
|---|---|---|---|---|
| Number of matches | 15 | 14 | 12 | 13.6 |
| Consistency rate (%) | 75 | 70 | 60 | 68 |

## V. EVALUATION EXPERIMENT FOR THE PROPOSED INTERFACE

### A. Purpose and Preparation

The purpose of the experiment was to confirm whether using the proposed interface makes it easier for the subjects to discover the characteristics of the play, to understand the movement trends, or to judge which character is advantage within a specific period of time. In this experiment, there were four patterns (Pat.1-Pat.4) in the video.

- Pat. 1 The move distance bar (including number of moves) and advantage annotation are both displayed
- Pat. 2 Only the move distance bar (including number of moves) is displayed
- Pat. 3 Only the advantage annotation is shown
- Pat. 4 The proposed system is not used

The content of the four videos (game content) watched by each of the subjects were different. There were 12 subjects (A-L), all of whom were new to observing games (not experts), but who knew the general rules of a fighting game.

### B. Procedures and Hypothesis

The procedures were as follows.

1) Ask the subject to watch the videos.
2) Ask the subject to respond to the questionnaire.
3) Change the video pattern (the four outlined in section V-A) and return to step 1.
4) After the subject has watched the 4 patterns of the video, they are asked to respond to a comprehensive questionnaire.

The hypothesis of this experiment is as follows.

- H1 Ease of identifying the characteristics of the moves
  Pat.1 $>$ Pat.2 $\fallingdotseq$ Pat.3 $>$ Pat.4
- H2 Number of characteristics of the moves identified
  Pat.1 $>$ Pat.2 $\fallingdotseq$ Pat.3 $>$ Pat.4
- H3 Ease of understanding the trend in forward/backward movement of the characters
  Pat.1 $\fallingdotseq$ Pat.2 $>$ Pat.3 $\fallingdotseq$ Pat.4
- H4 Ease of identifying the dominant character in a short period of time
  Pat.1 $\fallingdotseq$ Pat.3 $>$ Pat.2 $\fallingdotseq$ Pat.4

In addition, the questionnaire is not only a 7-point rating (7: Good, 1: Bad), but in step 2, also asks for comments on each of the four patterns of videos described in section V-A. As for the characteristics of the moves that have been identified, the subjects were asked to list the characteristics of each player. In addition, in step 4, the subjects were asked to comprehensively describe the pros and cons of the proposed system (if any), as well as to describe what other systems are needed (if any).

### C. Results and Considerations

Table II summarizes the results obtained from the subjects. The video patterns in Table II are the four patterns of video listed in section V-A (Pat.1-Pat.4). Identifying the characteristics of moves refers to identifying the techniques used by each player and the characteristics of their movements. The number of move characteristics identified refers to the number of move characteristics that the subject identified in the video. Ease of understanding the trend in forward/backward movement refers to how easy it is to understand the distance that each player has moved forward/backward, in addition to the number of times that the player has moved forward/backward. The ease of identifying the dominant character in a short period of time refers to how easy it is to see which character is dominant within a certain period of time (for this paper, 150 frames). The average score was calculated using the 7-point evaluation scale used in the questionnaire. The number in parentheses is the number of people with an evaluation value of 5 or more; that is, the number of people who clearly gave a positive evaluation.

In Table II, regarding the ease of identifying the characteristics of moves, the videos in Pat. 2, in which only the move distance bar (including the number of moves) is displayed and the advantage annotation is not displayed, had the highest rating. Pat. 1 videos were the second highest, thus hypothesis H1 was not satisfied. Looking at the comments, three out of four subjects who rated Pat. 2 higher than Pat. 1 provided negative comments for the videos in Pat. 1, such as "the advantage annotation was difficult to see and understand (E, G, K)." Therefore, we can assume that the rating for Pat. 1, which also visualizes the advantage annotation, has been lowered. In addition, it can be said that the advantage annotation is only a visualization of the result of a judgment made on move characteristics from one viewpoint, and while there was only a little difference in the average rating for the videos in Pat. 3 and Pat. 4, we could see a clear difference between them and

TABLE II
EXPERIMENTAL RESULTS

| Questionnaire item | Video | Ave. score |
|---|---|---|
| Ease of identifying the characteristics of moves | Pat.1 | 4.83 (7) |
| | Pat.2 | 5.17 (9) |
| | Pat.3 | 4.17 (5) |
| | Pat.4 | 4.00 (2) |
| Number of move characteristics identified | Pat.1 | 4.42 |
| | Pat.2 | 3.83 |
| | Pat.3 | 3.50 |
| | Pat.4 | 3.00 |
| Ease of understanding the trend in forward/backward movement | Pat.1 | 6.33 (12) |
| | Pat.2 | 6.33 (12) |
| | Pat.3 | 3.67 (5) |
| | Pat.4 | 3.50 (4) |
| Ease of identifying the dominant character in a short period of time | Pat.1 | 5.25 (8) |
| | Pat.2 | 4.42 (6) |
| | Pat.3 | 5.17 (9) |
| | Pat.4 | 4.08 (6) |

the average rating for Pat. 1 and Pat. 2. Based on the above, it can be said that it is necessary to improve the visibility of the advantage annotations, as well as to devise ways for users to discover the move characteristics from other viewpoints.

In terms of the number of move characteristics identified, hypothesis H2 was satisfied. Looking at Subject H's description, for the videos in Pat. 3 and Pat. 4, in which the move distance bar was not displayed, most of the descriptions were about attack methods and the techniques used, such as "attacks often" and "many grabbing techniques." On the other hand, for the videos in Pat.1 and Pat.2, in which the move distance bar is displayed, in addition to comments about the attack methods and techniques used, there were also descriptions of the character's movements, such as "not much advancement" and "although it seemed as though [the character] was retreating, it was also advancing." From this, we can assume that in the videos which displayed the move distance bar, the move distance bar was put to use in identifying move characteristics, and number of move characteristics identified increased. The following are possible reasons as to why hypothesis H2 was satisfied but hypothesis H1 was not. In this experiment, the subjects were not forced to look at the move distance bar or advantage annotations to identify these characteristics, and thus, subject E and others did not refer much to the visualization results of the proposed method, and instead attempted to identify characteristics only through the content of the game. It is for this reason that we believe the results did not support hypothesis H1, but did support hypothesis H2.

For ease of understanding the trend regarding the forward/backward movement of the characters, hypothesis H3 was satisfied. Looking at the free responses from subjects, typical comments for Pat. 3 and Pat. 4 videos, in which the move distance bar was not displayed, are described below.

- Positive Comments
  - I somewhat feel like I understand (F, H, L)
- Negative Comments
  - There is not enough time to see (the frequency of movements) (A, C, D, E)
  - I can see forward movements but not backward movements (G, H, J)
  - I am too focused on the technique to be aware of the movements (G, K)

In videos where the move distance bar was not displayed, there were many negative descriptions, most likely because the subjects are not usually aware of the movement trends of a character. Next, typical comments for Pat. 1 and Pat. 2, in which the move distance bar was displayed, are described below.

- Positive Comments
  - Easy to understand because the move distance bar and the number of movements is displayed (A-L)

There were no negative comments regarding the videos for Pat.1 and Pat.2. All subjects responded that the move distance bar being displayed made it easier to understand. This suggests that it made it easier for observers who are not conscious of a character's movement trends to understand the character's trends in forward and backward movement.

For ease of identifying the dominant character in a short period of time, hypothesis H4 was satisfied. Looking at the comments of the subjects, typical comments regarding the videos for Pat. 2 and Pat. 4, which did not have advantage annotations, are described below.

- Positive Comments
  - I decided that the character with successful combos was dominant.
  - I somewhat understand (B, F, G, H, I, J)
- Negative Comments
  - I can't tell when it is a close contest (J, L)
  - If there is no advantage annotation, I end up making a decision based on the present status of the stamina bar (A)

Next, typical comments for the Pat.1 and Pat.3 videos, in which the advantage annotation was displayed, are shown below.

- Positive Comments
  - It is easy to understand because of the advantage annotation (B, C, D, E, F, H, I, J, L)
- Negative Comments
  - The advantage annotation is difficult to see and understand (E, G, K)

Nine subjects stated that it was easy to understand because of the advantage annotation, and thus it can be considered that the advantage annotation made it easier to understand who was the dominant character in a short time. There were some negative comments that the advantage annotation was difficult to see, and thus it can be assumed that by improving its visibility in the future, it will be even easier to understand who is the dominant character. Additionally, one subject responded that "the number of times that the advantage annotation was displayed did not directly relate to the outcome of the fight, which was unexpected (D)." Based on this opinion, we have

found that the advantage annotation is effective in terms of finding something unexpected in the game.

Based on the above results of the experiment, it can be said that by using the proposed interface, it became easier to identify the characteristics of each play, the movement trends of the characters (forward/backward), and to identify the dominant character in a short amount of time.

## VI. Conclusion

In this paper, we have proposed an observer interface focused on the trends of character movement and stamina in fighting games. According to the evaluation experiments, it was found that using the proposed interface made it easier to understand the characteristics of moves, the movement trends of the characters, and to identify the dominant character within a certain period of time. Future tasks include improving the visibility of the move distance bar and advantage annotation, and examining techniques for discovering move characteristics from other perspectives.

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