Comparative Visual Gaze Analysis for Virtual Board Games

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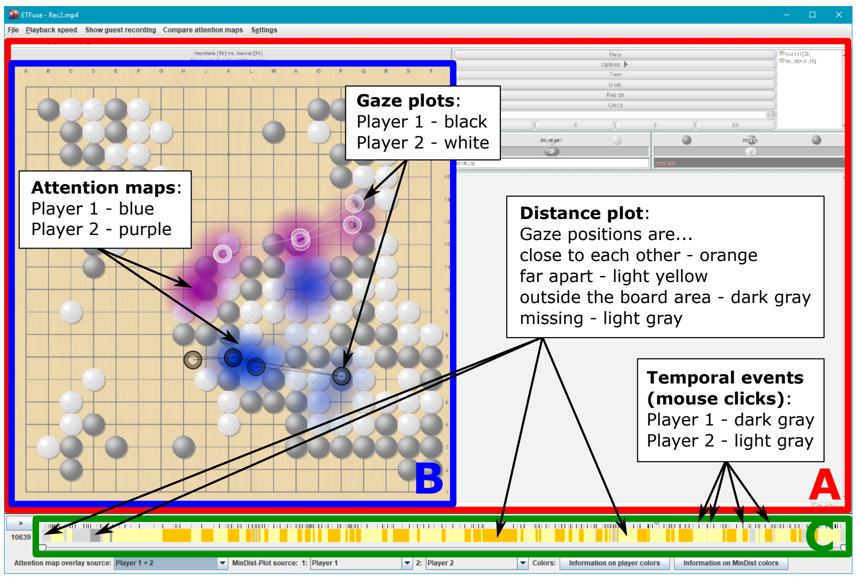

Figure 1: Interface of our visual analysis system for the eye movement data of two persons playing the board game Go. The main area (A) shows the screen content of the first player (black), which contains the board (B) and a control panel to the right. On top of the board, attention maps (blue and purple hotspots) and gaze plots (black and white circles connected by line segments) for a specific time frame for both players are shown. Below the main area (C), we provide a timeline highlighting important events as well as a distance plot that visualizes the proximity between the players' gazes.

ABSTRACT

We introduce an approach for the visual analysis of eye movement data of competitive virtual board games played by two persons. It provides methods to temporally synchronize and spatially register gaze and mouse recordings from two eye tracking devices. With our system, analysts can examine such fused data visually with a combination of techniques: attention maps and gaze plots as well as a temporal summary of the distance between gaze positions and mouse events of the two players. We show different test scenarios from the competitive game Go, which is especially complex for the analysis of strategies of individual players, to demonstrate our methods. In general, our visual analysis approach can provide analysts with insights into strategies, learning processes, and means of communication between people.

CCS CONCEPTS

• **Human-centered computing** → *Visualization design and evaluation methods*; *Visual analytics*; *Visualization techniques*; *Heat maps.*

KEYWORDS

Eye tracking, visual analysis, comparative analysis, board games

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1 INTRODUCTION

Eye tracking can be used in many different application areas and has become an established method for exploring different scenarios in traditional board games. Comparative analysis of people playing board games, against each other or together against another team, can provide insights into strategies, thinking and learning processes of players, as well as into the means of their communication. An example is the work of Charness et al. [2001], using eye tracking to explore perceptual aspects of chess experts and novices.

In this paper, we introduce a system for the combined gaze analysis of two players. The fact that eye movement data of players involved in the same online game are usually recorded on separate computers, perhaps using different eye tracking devices with different accuracy and sampling frequencies is challenging for such comparative analyses. It can be difficult and time-consuming to synchronize and compare such eye movement data. To the best of our knowledge, there exists no work on a synchronization and combined visualization approach for eye tracking data collected on independent and different hardware for multiple participants.

In our approach, the eye movement data of two players recorded on different devices can be synchronized and visually represented for analysis purposes. In the background, our system performs image-based matching and a coordinate transformation between data from two eye tracking systems. In addition, our system provides a suite of visual analysis options that enable domain experts to analyze and compare the attention of two players during the game. For example, analysts can compare attention maps shown for areas between important events or the whole match to detect local or global attention patterns of players. They can also compare the fixations of two players during specific time steps using a time-constrained gaze plot for a more detailed analysis. Furthermore, we provide a temporal summary of the distance between players' gaze positions, and the temporal position of mouse events, which enable analysts to identify potentially interesting time spans during which players were focusing on nearby or different positions. Figure 1 shows the system we have developed in which eye movement data is visualized for two players for comparative analysis.

We demonstrate the effectiveness of our approach by applying it to an online version of Go [Foundation 2019], whose complexity is provably larger than that of chess and its most complicated variant, Shogi. We focus on two scenarios: two players competing against each other, and two players collaboratively playing another team.

Our approach can provide insight into the thinking processes of the players during the game, as well as the experience and strengths of players. Through our use case, we are able to make a number of observations and gain insight into participants' strategies that would have been more difficult to make without using our comparative analysis of joint eye movement data.

This paper describes the technical application that we shortly presented as a demo in our previous ETRA demo paper [Munz et al. 2020] and is an extension thereof. We will particularly outline our technical implementation to achieve spatial and temporal synchronization for a combined visualization of eye tracking data of multiple participants.

Our system is implemented in Java. We will make our source code publicly available through GitHub.

2 RELATED WORK

We discuss the two research areas related to our work: eye tracking in the context of games and visualization of eye movement data.

Eye Tracking for Games. Eye tracking for games [Almeida et al. 2011] has become increasingly important in recent years, as discussed, for example, in EyePlay [Turner et al. 2014]. Related work can be separated into research on live systems communicating gaze positions between people and research on post-study analysis.

Smith and Graham [2006] investigate gaze as an input modality for video games but do not consider gaze as a visual cue for other players. Sundstedt [2012] gives a general overview of gaze input in games. Isokoski et al. [2009] provide multiple examples for gaze controlled games with the board game Go as an example. Lankes et al. [2016] and Newn et al. [2018, 2017] provide gaze visualizations to players of a competitive board game and analyze how this cue influences their strategies. Maurer et al. [2016] conduct similar research on collaborative games and Niehorster et al. [2019] on collaborative and competitive visual search tasks. Furthermore, Vertegaal [1999] presents a live system for gaze-aware communication between multiple people. Related work focuses on including gaze into remote scenarios, for example, to improve avatar communication or collaboration [D'Angelo and Gergle 2016] and teaching [Špakov et al. 2019b; Yao et al. 2018] scenarios. Further, Špakov et al. [2019a] use a VR context and share the focus between two players. The analysis of recorded gaze for post-hoc analysis is not the focal point of the aforementioned publications. Our work does not focus on gaze-aware communication but aims at providing detailed spatial and temporal analysis methods to investigate gaming scenarios with two players. However, because spatial and temporal matching between data sources is performed automatically, we see the potential of our approach to also be applied for live visualization of gaze, for example, in training for complex games, similar to EyeChess [Špakov 2005].

Gaze is a valuable component for game analytics [El-Nasr et al. 2016], investigating the players' strategies and behavior [Sundstedt et al. 2013]. However, there are far fewer approaches that focus on the analysis of eye movement data from games, than approaches for interaction. Choi and Kim [2017] and Almeida et al. [2010] analyze gaze distributions in first-person shooter games. Jermann et al. [2010] use dual eye tracking and analyze with descriptive statistics the gaze of two persons playing a collaborative game. Shvarts et al. [2018] synchronize and analyze data collected from head-mounted eye-tracking devices. Charness et al. [2001] compare expert and intermediate chess players' strategies, but they do not investigate the dynamics between players' gazes during a game. Kumar et al. [2018] perform a visual analysis of checker games, focusing on the analysis of gaze distributions. Hessels et al. [2018, 2019] analyze gaze of people looking at each other. In contrast, we introduce an approach to spatio-temporal analysis with specific comparison methods that help effectively analyze two players together.

Visualization of Eye Movement Data. Visualization plays an important role in assessing statistical results and in data exploration for hypothesis building. A survey of different techniques for eye tracking visualization is provided by [Blascheck et al. 2017]. Based on a taxonomy of eye tracking analysis tasks [Kurzhals et al. 2017], techniques that enable the comparison of players viewing the same stimulus include timelines, attention maps, or gaze plots.

Timeline visualizations show the temporal evolution of gaze information. For example, gaze stripes [Kurzhals et al. 2016] display a portion of the stimulus around a fixation as a timeline. However, we cannot use this technique because the stimulus snippets would be too similar due to the regular shape of a board game. As we are interested in the temporal similarity and difference of the participants' focus, we use a comparative timeline visualization. Additionally, we apply attention maps [Holmqvist and Andersson 2017] independently for both participants and show them on top of each other as overlay on the stimulus to enable the exploration of differences and similarities. Gaze plots [Noton and Stark 1971a,b; Yarbus 1967] show the spatio-temporal order of fixations and saccades on a stimulus. This leads to visual clutter if gaze plots of all participants are depicted together. However, if only selected participants are compared or only short time spans are analyzed, in addition to animated changes [Weibel et al. 2012], this technique enables analysts to compare eye movement data of participants on animated stimuli. This technique is useful in our approach, to explore and compare the reaction of sudden changes in the stimulus.

3 REQUIREMENTS

The goal of our approach is to provide a way to analyze and compare eye movement data from two players who play collaborative and competitive board games against each other. The dynamic stimuli show the same game play to both participants, albeit on different computers that the participants are using to play against each other. This means that each player sees—at least for the most part—the same screen content, and for each player, the eye movements are recorded independently with stationary eye trackers. The input data required for our approach are gaze positions, screen recordings, and temporally logged events (e.g., mouse clicks) from each participant. Such data might be obtained from recording devices with different hardware (screen resolution; sampling rate of the eye trackers), and the recordings might have started at different times. Therefore, the data has to be temporally synchronized and mapped to a common screen area for the analysis. The following aspects have to be considered:

- **A1** Bi-directional mapping of gaze to the screen recordings
- **A2** Temporal synchronization of data
- **A3** Handling different recording frequencies

After fusing the data, we support visual analysis with appropriate visualizations and interactions to explore interesting areas of the recordings. As a team of visualization researchers, eye tracking experts, and an experienced Go player (2-dan amateur player) who supported us in the analysis of our collected data, we identified the following requirements to compare eye movement data of multiple participants and support the visual analysis:

- **R1** Subdivide time into intervals defined by important events that can be extracted from logged data (e.g., when a player performs a mouse click to put a stone on the board).
- **R2** Mark additional temporal positions (e.g., of interest to the analyst) and use for subdivision into intervals.
- **R3** Identify temporal areas for the analysis (e.g., during which gaze positions of multiple participants are close together).

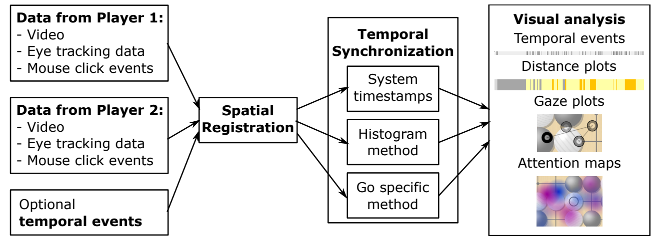

Figure 2: Overview of our visual analysis approach.

- **R4** Allow visual comparison of gaze positions of multiple participants (e.g., with gaze plots and attention maps).

4 VISUAL ANALYSIS APPROACH

With our visual analysis approach, the comparison of eye movement data of two participants is possible. In the following, we outline our automatic approach to prepare eye movement data for analysis (A1, A2), and our visualization concepts for visual analysis (R1 – R4) to detect and analyze interesting temporal and spatial areas within the recordings. Figure 2 shows an overview of our approach.

4.1 Image-based Mapping and Synchronization

As first step, the eye movement data from the two players has to be spatially registered (A1) and temporally synchronized (A2). Both can be achieved automatically by exploiting image properties of the recorded videos.

Spatial Registration. For the spatial mapping (A1), a coordinate transformation of the eye movement data of one of the players is performed to fit the recording for the other player. We model this mapping as an affine transformation and restrict it to the crucial part of the application for the analysis: the game board. For both players, the boards may be shown in different sizes at different positions on screens with different resolutions and aspect ratios. The remaining area on the screen may show different content for both players, such as additional graphical interface elements (e.g., a chat area) that is ignored from the mapping. In the analysis, users have to keep in mind that just the video of one player is shown. When eye movement data from the second player is shown outside the specified region, he may look at different screen content as the current video suggests. The analysis could be limited to the relevant cutout; however, we believe that it is still interesting to differentiate if a player looked somewhere else on the screen or if eye tracking data was not available at all.

Temporal Synchronization. We developed three methods to temporally synchronize (A2) the videos and eye tracking data of two players. We assume that there is synchronization between the video and the eye movement data for each individual player.

A simple approach is the use of *system time stamps*. The accuracy of the synchronization depends on the quality of the system time on the individual machines that were used with the eye tracker software. In our experiments, we observed time differences between 0.3 and 5 seconds. To achieve higher accuracy, it would be possible to set up an additional time synchronization between the two machines, however, this would make our approach less flexible.

A more accurate result can be achieved with our image-based *histogram method*. Here, the goal is to identify the first frame in both videos that matches a given board configuration. Histograms are calculated for the individual color channels and used to compare images for their similarity [Cha and Srihari 2002]. There are multiple methods available to compare histograms [Cha 2007]; we use the Pearson correlation coefficient as a measure [Team 2014]. Our approach tries to find the first frame of a new board configuration (i.e., after putting a new stone on the board) by comparing histograms for the area of the board. With increasing screen resolution, the reliability of histogram comparison decreases as the number of images with similar histograms but different content increases. To avoid this problem, the frames of each video are divided by a grid into multiple cells to calculate and compare multiple histograms for each frame. For the selection of the grid size and the thresholds to detect similarity, it has to be considered that mouse cursors and half-transparent preview stones may influence the comparison and create wrong results. The first frame of a new configuration is found by repeatedly comparing with previous frames until the histogram dissimilarity is above a certain threshold. Once this starting frame is found in the first video, we compare its histogram with frames from the second video until the earliest most similar frame is found. This approach also enables support of other games than Go and even other stimuli than games.

We developed a third method that makes explicit use of the context of a board game with the goal to find the frame when a specific stone was placed on the board in both recordings. The colors at the positions of the stone are compared for frames of the first video to detect when the stone was put on the board. Next, our method looks for the same color change for this stone in the other video and uses the time difference between both videos for synchronization. As before, mouse cursors and preview stones may influence the result. To avoid wrong synchronization that may be introduced by a color change of the mouse cursor, our method checks the color on two different positions on a stone, and the detection mechanism is based on a minimum color change. While this approach was designed for Go, it can also be used for other games such as chess, or other board games in which a sudden change of color for a specific position can be used for synchronization. This approach usually creates the most accurate results but may occasionally fail due to some different screen content (e.g., mouse cursor, preview stones, different texture of stones/board) that is shown on different machines.

The latter two methods may use the system time stamps to increase performance by providing estimated time stamps to find initial frames in the second video. This also avoids wrong synchronization results if the same board configuration is reached multiple times. Due to some varying time delay for the appearance of new elements resulted from the network connection, it is not possible to exactly match the videos of the two players. We observed a common delay for the appearance of new elements in the area between 0 and 0.2 seconds after the synchronization; this delay may occasionally be larger due to the network connection.

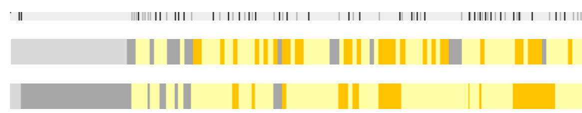

Figure 3: (a) Timeline with positions of mouse clicks (lighter color for one player and darker color for the other one). (b) Distance plot temporally subdivided by equal intervals of two seconds, and (c) by mouse clicks of both players.

4.2 Visual Comparison Methods

Our visual analysis approach combines several visualizations for the analysis of collaborative and competitive content: a distance plot (R3), a timeline highlighting important events (R2), gaze plots (R4), and attention maps (R4). For temporal subdivision, mouse clicks (R1), logged by the eye tracking system, are processed, and analyst-defined additional temporal events (R2) are taken into account. Figure 1 shows the graphical interface of our visual analysis system.

Mouse Clicks and Custom Events. In a timeline, we highlight the position of important temporal events (R1, R2). The placement of a new stone is often connected with a change of attention for the players. A player triggers these events with a mouse click. The eye tracking system logs such events, and it is possible to visualize their temporal position (see Figure 3 (a)). Further events can be added manually to show them in the analysis. This is especially useful if interesting things happen on the screen that are not influenced by the two players. An example is when the players play against further opponents whose data is not recorded. These events are shown in custom colors and can be used to subdivide the timeline into intervals (R2) for the distance plot and for updating the attention maps (see next paragraphs).

Distance Plots. Below the timeline for events, we use a 1D plot to visualize the distance between the gaze positions of two players (R3). This visualization is helpful to detect periods when players look at positions on the board that are close to each other. First, we divide time into intervals. This can be done for predefined equally sized time periods or according to specific events (see Figure 3 (b) and (c)). Then, we assign each interval the color of one of four categories. Light gray is used when no eye movement data was available within the interval for at least one player. This is often visible at the beginning or end of the timeline because the players usually start and stop their recordings at different times. Additionally, it may indicate that players looked away, closed their eyes, or, if intervals are small, that they blinked. Such areas at the beginning and end can often be ignored for the analysis as only data from one player is available. If most of the gaze positions are outside the board, dark gray is used. Light yellow indicates that the distances between the gaze positions of both players on the board were mostly above a threshold. In all visualizations of this paper, we use a threshold of 150 pixels, which equals about three cells on the board. Orange highlights periods during which the distance was mostly below this threshold. As the frequencies of both recordings may differ, it is not possible to directly compare gaze positions. Instead, we upsample the lower-frequency data to then compare them to the gaze positions of the data recorded at the higher frequency (A3).

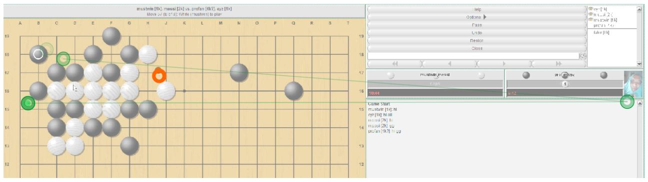

Figure 4: Rengo game. Player 2 (orange fixation), is looking intensely at one part of the board. Player 1, while also checking the board, glanced at the picture of a player on the opposing team (green circle on the right side).

Gaze Plots. A gaze plot is well known for static images but also used dynamically for video material (R4). As our stimulus changes over time, we show new gaze information in real-time. To keep track of the previous fixations, some previous fixations can also be visualized. In our approach, we show joined gaze plots of multiple players, in which all fixations are drawn by circles connected by straight lines representing saccades (see Figure 4). The most recent fixation is more opaque than the previous ones.

Attention Maps. Attention maps, also well known as heatmaps, are often better scalable for visualization of a large number of gaze positions. They highlight areas where people focused on most. In our system, we generate the attention maps for fixations within a specified interval. It is possible to show the attention map of only one player or multiple players as overlays (R4). To show multiple attention maps simultaneously, each player is represented by a distinguishable color whose alpha channel goes from opaque to transparent. Figure 5 shows an example in which blue is used for the attention map of one player and purple for the other player. The time interval for the calculation of attention maps can be an analyst-defined interval (e.g., for the entire time of a match) or for multiple predetermined intervals to show dynamic changes of the attention. The previously mentioned logged and manually specified temporal events can be used to calculate attention maps between every two events and to update the overlay according to the current temporal position.

5 USE CASE – GO

To demonstrate the effectiveness of our approach, we apply it to Go, the oldest known board game in human history whose rules have not changed since its inception. Go has very high state-space and game-tree complexities [Wikipedia contributors 2019] and has been recently solved (i.e., AI programs defeating the strongest human players) by *AlphaGo*, a software developed by Deep Mind based on deep learning [Silver et al. 2016, 2017].

The standard Go board contains a 19 × 19 grid, on which the two players take turns to place a stone of their respective color (black or white). Stones already placed on the board by one player can be *captured* by the other player under certain conditions. At the end of the game, both players count their respective *territory*. The player with more points wins the game. In addition, Go can be played between two teams of players, called *Rengo* [Sensei's Library contributors 2019]. Typically, each team consists of two players that take turns to place stones of their color on the board.

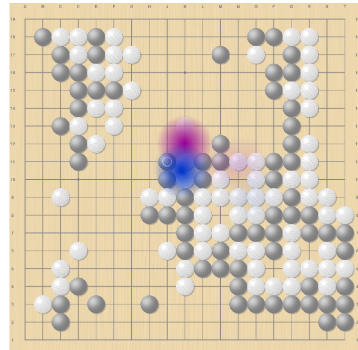

Figure 5: Player 1 (black) is focusing on the two white stones in the center of the board (blue hotspot) and is ready to capture them, which would end the game. Player 2 is focusing on the *only* escape route for the two white stones.

In the following, we use the results from some play scenarios as illustration for the capability of our system and to demonstrate how our system can be used to explore the behavior of participants playing board games. To reveal proper patterns from the board game Go, a more extensive user study would be required.

Some possible questions that can be explored:

- **Q1** Is there a difference in focused areas between players, reflecting their intentions, experience or styles?
- **Q2** Do players know what they want to do next or do they have to think about multiple possible next moves?
- **Q3** Is a player focused while it is the other player's turn?

5.1 Data Acquisition

We collected data from several Go matches during which two volunteers played the virtual board game KGS Go [Foundation 2019] via internet connection against each other or in collaboration against two other opponents whose eye movement data was not recorded. The first player has a strength of 1-kyu, which puts him at the top of the bracket of *intermediate amateurs* and the second player has a strength of 2-dan, which puts him in the bracket of *advanced amateurs*. We used two different remote eye tracking devices to record the data, which differ in their recording frequency and monitor resolution. The first device was a Tobii Pro Spectrum 1200; it has a screen resolution of 1920 × 1080 pixels, eye movement data was recorded at 1200 Hz, and the Tobii Pro Lab software was used to record the eye movements and the screen. The second device was a Tobii T60XL; it has a screen resolution of 1920 × 1200 pixels, recorded at 60 Hz, and Tobii Studio was used to collect all data.

The recordings were collected in a lab space isolated from outside distractions. Calibration and recording ran independently for both participants on their devices, and the players started a match once everything was set up. The participants played different types of matches against each other, leading to a variety of different game scenarios for the analysis. Each match had a duration between 4 and 11 minutes, and matches were performed on different grid sizes.

The more experienced player (in the following Player 2) always played the white stones, whereas the other one (Player 1) played the black stones. As it is common in Go to start with black stones,

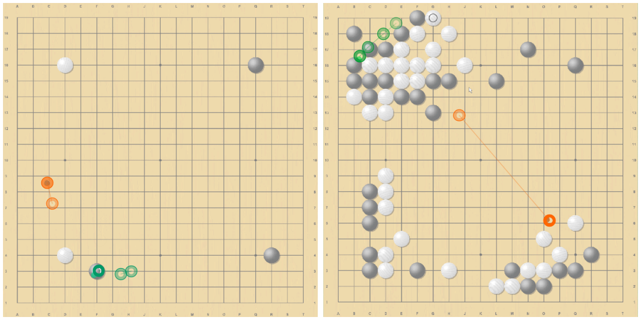

Figure 6: Rengo game. Left: After the opposing team had approached the white stone at the lower-left corner, the two participants' eye movement data shows their different styles of response. Right: After having strengthened their group that contained the stone with an inscribed black circle, both participants were planning an attack. Their gaze reveals that they were focusing on different targets.

Player 1 had the first move in each match. In Rengo, both players used white stones. The color of an attention map, when the maps for both players are shown simultaneously, is blue for Player 1 and purple for Player 2. In Rengo, Player 1 has green fixations, whereas Player 2 has orange ones.

5.2 Visual Analysis

In this section, we demonstrate the effectiveness of our approach. A co-author of this paper, who is a 2-dan amateur player (advanced amateur), performed the data analysis. Additionally, we showed our observations to the players and collected their feedback. The findings we describe in the following are from the Rengo game and one of the competitive matches; a 19×19 grid was used for both games.

When exploring the eye tracking data, we could detect quite different playing styles [Ishida and Davies 1979] for both players (Q1) and observe their reading process during games [Jasiek 2015]. In several games, we consistently observed an attack-oriented style of Player 1 and a defense-oriented style of Player 2. Both their thinking process and intentions differed in such scenarios, which might also be influenced by their strengths in the game. After we informed the players about or findings to their playing styles, they both said that it made sense. However, they were surprised that the eye tracking data was able to capture this information. An example is visible in Figure 6 (left). During the Rengo game, the black team had attacked the white stone in the lower left corner. Both players agreed that a local response was needed, but with different strategies (Q1). Player 1 (green fixations) was in turn and considered attacking the black stone by pincering it. Player 2 (out-of-turn) focused more on a position opposite the black stone to support the white stone. This difference in the attention would not be that easily visible without visualization of the synchronized data.

Figure 6 (right) shows a further situation during the Rengo game where the players had different intentions (Q1). Right after the white team had captured a key black stone in the upper-left, the two participants were considering ways to leverage on their newly gained strength to attack nearby black groups. Player 1 (green fixations) was exploring to capture the black group in the corner, while Player 2 (orange fixations) was considering attacking the black group on the outside, for which more points could be made.

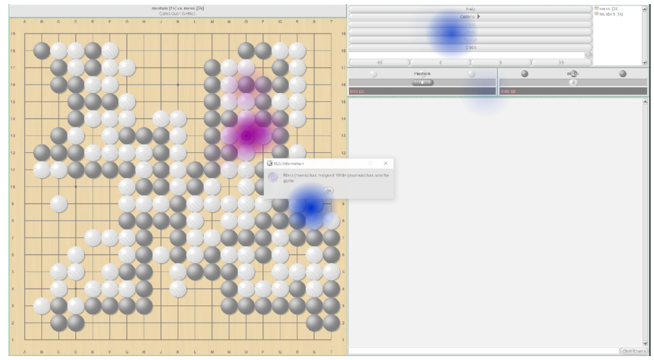

Figure 7: Player 2 (white) played the stone (purple hotspot) to win the game and his focus remains on this position on the board. Player 1 is looking at the resign button (blue hotspot on the top) and the dialog that appears after pressing the button (blue hotspot in the center).

Another example is visible in Figure 5; it shows the joint attention map during a game in which the two participants played each other. The game was at a crucial stage, with two white stones being the center of a fight. Both players have their attention around the same place. Yet, Player 1 (black) is looking at the two white stones (blue hotspot) and is ready to capture them and end the game. However, it was the turn of Player 2, whose attention (purple hotspot) is fixed at the grid above, which was the only escape route for his two stones. It is visible that Player 1 also thinks about a possible next move as if it was his turn and not about a possible response of Player 2 (who actually is in turn) to his previous move.

Additionally, we noticed in most matches that the attention maps for the entire match (or larger time spans) showed that Player 1 looked at broader areas of the board while Player 2 focused more on specific regions (Q1, Q2). For example, in the competitive matches Player 2 mostly focused on the bottom right part of the board. While Player 1 also focused on this region, his gaze was generally more spread, also toward the top of the board. In the Rengo game, the difference between this focus was also visible. Especially at the beginning of the match, both participants focused on different areas, and only later, the areas they focused on became quite similar.

Exploring the attention maps of the players revealed further patterns in the focus of the players (Q1, Q3). For example, at one point during the Rengo game (Figure 4), it was the turn of Player 2. While he was carefully considering how to proceed with the local fight (focused gaze indicated by the sole orange circle on the top middle of the board), Player 1 (on the same team but out of turn) was also examining the local situation. Yet, his gazes at the upper-left corner of the board sandwiched a quick glance at one of the opposing player's icon on the right side of the interface (green fixations). This quick change of attention was probably due to two factors: Player 1 was not in turn, so there was less pressure on him, and he was a younger player and could be distracted more

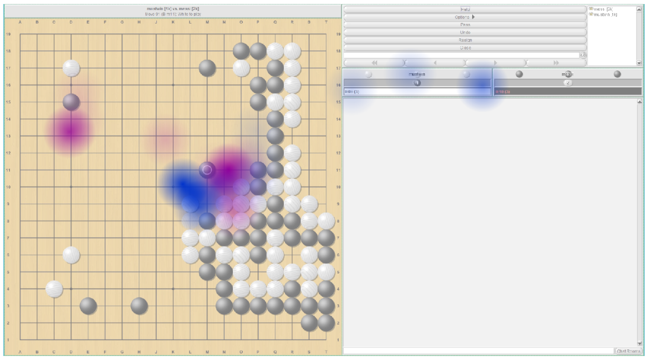

Figure 8: After the two players were engaged in a *semeai* (Go term for a capture race) the fight resulted in a *seki* (both groups live). Both players recognized this outcome and immediately shifted their focus to other parts of the board.

easily. Player 1 laughed when we showed him that we recorded him looking at the opponent's icon. He said, he was curious about people's KGS names and icons. If they look interesting, he would consider playing more games with them. With our approach, it is easier possible to make such observations because it is possible to study the eye movements of both players simultaneously and not with two separate recording streams.

Another interesting observation could be made in the same game, as shown in Figure 7, where both players drew the same conclusion from the current situation but with different behavior (Q1). Player 2 placed a stone (below the purple hotspot) to get his stones back to safety and win the game. Afterward, his eye movement stayed on this spot, and he looked nowhere else because the game was over. At the same time, Player 1 (blue hotspot) looked at the resign button and the dialog that appeared after pressing the button. Despite the relatively large distance between the areas of attention of both players, their conclusions regarding the game were the same.

Finally, we noticed that both players have the habit of controlling their own and the opponents' remaining time. To keep track of the time and avoid rushed decisions, they both frequently checked the time by looking at the control panel; this may look like they are not paying attention to the board.

5.3 General Observations

In the analysis, we mostly focused on gaze plots and attention maps. It was easier to keep track of them as they are shown on the board, and it is possible to monitor the game situation simultaneously.

We experienced that gaze plots are more effective than the attention maps for this use case because the former show not only the exact grid points that have been focused on but also the sequence in which these grid points were gazed at. As an example, in Figure 4 the gazes of Player 1 shifted from the board to an opponent's icon and back. The attention map can show the two areas that the player focused on but does not show the back-and-forth shift in his focus.

In contrast, the attention maps appear to be more stable as they were time-averaged. Moreover, they can provide a better summary for multiple gaze points than the gaze plots. For example, in Figure 8, the attention of Player 1 had spread over six different parts of the board and interface, including checking the remaining time for his team. Such information would be difficult to find from the gaze plots that we are using to see the current eye movement of both participants and is thus limited in the number of fixations.

When studying the attention maps for the entire duration of a match, we noticed for one of the 19×19 competitive matches that attention maps cover grid points that were eventually occupied. This shows that places, the players considered as a possible next move eventually become the next move. Another observation is that places where heavy local fights occurred, tend to be covered by the attention maps. Additionally, as mentioned before, differences between the players and the focused areas could also be detected. We have the hypothesis that professional players could use such maps to spot blind spots of amateur players.

The distance plots were also useful in the analysis. At the beginning of the game, when the board is relatively open, the player's choices of a next move are largely dependent on their level and style; this is when their attention diverges the most. However, in the middle and end of games, players are engaged in local fights that attracts their attention to the same part of the board. In such cases, we can see areas in the distance plot that indicate that gaze positions of both players are close together (orange highlighted). Of course, when a local fight is settled, the players are open to decide where the next move is, thus styles set in again with diverging gazes (light yellow). We believe that this feature could be used in more extensive user studies to quickly find areas of local fights or areas when players are distracted by the chat area or not looking at the screen at all, and to explore the duration of such events.

It was essential for the analysis to see when mouse clicks were used to place new stones. The event timeline can also provide a sense of how quickly a player responds when it becomes his turn. For instance, when the game is in a complicated situation, players might think more. Overall, Player 1 spends less time between moves than Player 2, probably because he is younger or more spontaneous.

When we showed the recordings to the players, they liked the attention maps and gaze plots the best. After understanding the distance plots, they were interested in the Rengo game and wanted to know how much they agreed with each other. Player 2 wanted to also find out where and why they disagreed and hypothesized that they were different because he was stronger.

We admit that some of the patterns we found can also be seen in the placement of new stones. However, if we analyzed only data of newly placed stones without gaze information, it would, for example, not be possible to observe whether players explored same or different regions of the board, think about their own next moves or the ones of the opponent, explored a broader area of the board or focused on smaller regions and would play alike or differently, if it was the other player's turn. Especially in collaborative games, we see a high value of the additional information from eye movements as only moves of one player are visible by the appearance of new stones and not what the intention of the other player might have been.

6 CONCLUSION

We presented a new approach for the combined visual analysis of eye movement data from two players in virtual board games.

Data recorded with two independent eye tracking systems can automatically be spatially mapped to the same board area and temporally synchronized for a visual comparison of both players. The mapped and synchronized data can be visually analyzed based on mouse clicks and custom events using a distance plot, which provides a temporal summary of the distance between player's gaze positions, attention maps showing the overall or time constrained attention, and gaze plots of specific time steps for both players. Our use case demonstrated that different strategies of the two players could be extracted. Such intense and contrasted focus by two players would be impossible to observe without using such a synchronized visualization approach.

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