

Toward Post-Game Reflection in In-Person Collectible Card Games: Match Reconstruction Using Chest-Mounted Cameras

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Abstract. Post-game reflection is important in competitive games, but reviewing an in-person CCG match from memory alone is difficult. Rather than evaluating the effectiveness of post-game reflection itself, this study examines whether hand information and play-area changes in ordinary paper-card play can be reconstructed as a reviewable match log using chest-mounted smartphone cameras. Through an evaluation using Pokémon Trading Card Game match footage, we show that the method can detect hand cards and play-area cards with relatively high accuracy and partially reconstruct events and state changes. At the same time, the results reveal limitations caused by field of view, occlusion, and complex hand changes. These findings suggest that chest-mounted match reconstruction can provide cues for post-game discussion.

Keywords: Collectible card games · Post-game reflection · Chest-mounted cameras · Match reconstruction

1 Introduction

Reflection is an important learning process through which people reinterpret their experiences and apply them to future actions [13]. In competitive games, post-game reflection and post-game visualizations can support players in reviewing match events, understanding strategies, and improving future play [24, 12]. This study focuses on post-game discussion, in which players review a match after play by revisiting each point’s available options, actions, and results.

However, accurate post-game discussion is difficult in in-person collectible card games (CCGs). CCGs involve hidden information, complex game structures, diverse card types and zones, and interactions among card effects [17]. In particular, a player’s hand represents the options available at each decision point, while the play area shows the results of the actions taken. When players rely only on memory, it can be difficult to reconstruct the sequence of actions and state changes in sufficient detail, making it difficult to share the overall flow of the match during post-game discussion [5]. Therefore, in-person CCGs require a reviewable record of hand and play-area changes.

One possible response to this problem is to use digital CCGs or tablet-based play, where structured match logs can be obtained from the system. However,

this study does not argue that computer vision is necessary for such digital environments. Rather, it addresses ordinary in-person paper-card play, where no automatic match log is produced while players physically hold, play, and arrange cards. Switching to a digital or tablet version would change the play setting itself and therefore would not solve the recording problem of existing paper-card play. Prior work also suggests that physical play cannot always be treated as directly interchangeable with digital versions, and that tactile handling of physical cards can contribute to presence and realism [2, 6]. Therefore, this study targets in-person paper-card play and explores a lightweight method for recording changes in players’ hands and the play area without replacing the original setting.

This study examines whether first-person footage from chest-mounted smartphone cameras can be used to generate a reviewable match log that includes hand and play-area changes for later post-game discussion. Although chest-mounted cameras can be introduced with minimal equipment, they provide incomplete observations due to occlusion, camera angle, player posture, hand movements, and partial visibility. Therefore, this study does not aim to completely reconstruct the entire game state. Instead, it examines how much of the match flow can be reconstructed as a reflection-oriented match log in practice.

The contributions of this study are twofold. First, we propose a lightweight match reconstruction approach for in-person CCGs that uses players’ chest-mounted smartphones to generate a reviewable match log including hand and play-area information. Second, through an evaluation using real match footage, we report what hand and play-area information can be partially reconstructed and identify practical limitations in ordinary in-person paper-card play.

2 Related Work

Post-game reflection and visualizations. Prior work has discussed reflection in games as a process through which players reinterpret their experiences and connect them to learning and self-understanding [13, 23, 12, 14]. In post-game contexts, records, replays, and visualizations can support players in reviewing action sequences and recalling play experiences [24, 5, 20, 11, 16, 8]. Building on these findings, this study focuses on generating a match log for reflection in in-person CCG play, where digital gameplay logs are not automatically available.

CCG complexity and match-log analysis. Collectible card games (CCGs) are difficult to understand and analyze because they involve hidden information, diverse card effects, complex turn structures, and multiple zones [17, 3, 1, 4]. However, many existing studies assume the availability of digital logs or structured game states. In ordinary paper-card play, changes in players’ hands and physical card movements must instead be reconstructed from the play situation itself. Therefore, this study reconstructs observable match flow rather than computing optimal moves or predicting match outcomes.

State recognition in physical games. Image-based recognition in physical games has addressed chess, poker, bridge, and playing-card recognition [25, 9, 18, 7, 10,

26, 15, 19]. These studies demonstrate the feasibility of recognizing physical game components, but they mainly target structured boards, public information, or relatively controlled environments. In contrast, in-person CCGs involve flexible card layouts, overlapping cards, and players’ hands, making it difficult to reconstruct the match flow from public play-area recognition alone. Therefore, this study uses chest-mounted smartphone cameras as a lightweight approach for recording not only the play area but also players’ hands.

3 Approach: Chest-Mounted Match Reconstruction

3.1 Design Rationale

To generate a match log for later reflection in in-person CCGs, the recording method should capture each player’s private hand, capture public play-area changes, and be easy to introduce into ordinary play environments. A fixed overhead camera can capture the public play area in a stable manner, but it requires recording equipment and installation space. It is also difficult for such a camera to capture hand cards, because players usually hold their hands facing themselves. Therefore, fixed-camera setups are insufficient for generating a match log that includes private hand information.

This study therefore adopts chest-mounted smartphone cameras as a practical recording approach. As shown in Fig. 1, recording from around the chest makes it possible to capture the player’s hand when they check their cards, while also recording play-area changes when cards are played. We also considered head-mounted recording as another first-person approach, but in preliminary trials the footage fluctuated greatly due to head movements, making it difficult to stably capture both the hand and the play area. We therefore adopted chest-mounted cameras as a practical trade-off among hand visibility, play-area visibility, view-point stability, and setup burden. We do not claim that chest-mounted cameras are the optimal camera placement; rather, we treat this setup as a lightweight input condition for examining match-log reconstruction in in-person play.

At the same time, footage obtained from chest-mounted cameras is incomplete because it is affected by camera angle, player posture, hand movements, occlusion, and objects moving outside the frame. Therefore, this study does not aim to completely reconstruct the entire game state. Instead, it aims to organize observable hand and play-area changes from incomplete first-person footage and generate a reflection-oriented match log for post-game discussion.

3.2 Detection Targets

This study focuses on the Pokémon Trading Card Game and treats hand cards and play-area cards as the main recording targets. These targets are important for reviewing what options were available at a given moment, what actions were taken, and how the play-area state changed during post-game discussion.



Fig. 1. Example of the chest-mounted camera setup and captured match footage.

For hand cards, the system records cards currently in the hand, cards newly added to the hand, and cards used from the hand. For the play area, the system targets cards placed in the Active Spot and on the Bench, and records major changes such as Pokémon placement, switching, and Energy attachment. Together, these targets form the basis of the generated match log.

3.3 Detection and Match-Log Generation Pipeline

For object detection, we use YOLOv8 [22]. We trained two models: a hand-card detection model and a play-area card detection model. Training images were collected from chest-mounted camera footage captured in actual match environments and annotated with bounding boxes using labellmg [21]. The dataset contained 1,600 hand and 3,000 play-area images for 18 card types.

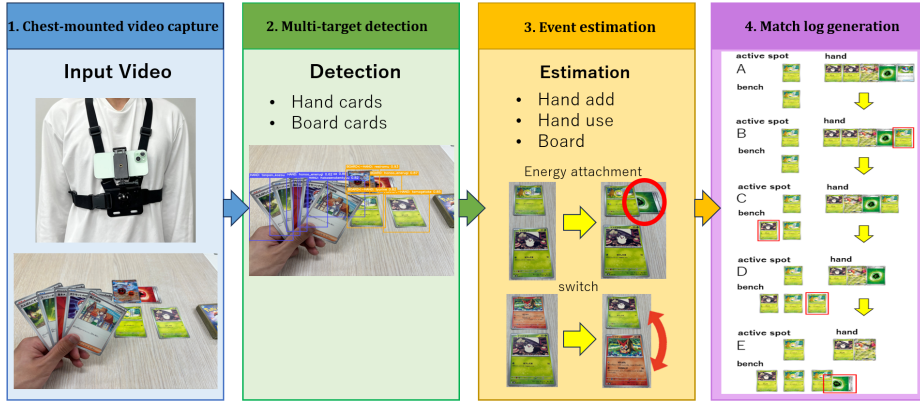
Fig. 2 shows the match-log generation process. The proposed method consists of four stages: video acquisition, card detection, state-change estimation, and match-log generation. First, the trained detection models are applied to chest-mounted camera footage to obtain frame-level detections of hand cards and play-area cards. Next, detection results across multiple frames are integrated to estimate changes in the hand and play-area states. Finally, the estimated changes are arranged chronologically and output as a reviewable match log.

Because chest-mounted footage is incomplete, the proposed method integrates observations across multiple frames rather than relying on single-frame detections. It estimates hand additions and uses, and organizes play-area changes in the Active Spot and Bench, including Energy attachments. Rather than producing an official complete game-state record, the resulting log arranges these observable changes chronologically as cues for post-game discussion.

4 Evaluation

4.1 Experimental Setup

We evaluated the proposed method using video footage from 15 Pokémon TCG matches captured with chest-mounted smartphone cameras. The first author



Card images: ©1995–2026 Nintendo/Creatures Inc./GAME FREAK inc.

Fig. 2. Overview of the proposed pipeline and the generated match-log format.

Table 1. Card-detection performance.

Target	Precision	Recall	F1-score
Hand cards	0.92	0.91	0.91
Play-area cards	0.79	0.93	0.85

played three matches with each of five collaborators, and both players wore chest-mounted smartphones during each match. The evaluation footage was not included in the training or validation data used for the detection models.

We conducted two quantitative reconstruction evaluations and one separate exploratory observation. First, we evaluated hand-card and play-area card detection using manually annotated frames. We randomly sampled 500 frames from the evaluation footage, consisting of 250 from the first author’s footage and 250 from the collaborators’ footage. The metrics were precision, recall, and F1-score.

Second, we evaluated match-log reconstruction accuracy by comparing generated logs with manually created ground-truth logs. We focused on hand-registration events, hand-usage events, Pokémon placement changes, and Energy attachments, because these events represent available options, actions taken, and resulting play-area changes. For hand-related events, we report results separately for the first author’s and collaborators’ viewpoints to examine the effects of camera angle, posture, and familiarity with the setup.

4.2 Detection Accuracy of Cards

Table 1 shows the detection accuracy of the card detection models. Hand cards achieved an F1-score of 0.91, while play-area cards achieved an F1-score of 0.85. These results indicate that chest-mounted footage is useful for reconstructing private hand information and public play-area states, although play-area detection was more affected by distance, occlusion, and crowded layouts.

Table 2. Reconstruction performance for hand-registration events.

Viewpoint	Precision	Recall	F1-score
First author	0.61	0.82	0.70
Collaborators	0.55	0.42	0.47

Table 3. Reconstruction performance for hand-usage events.

Viewpoint	Precision	Recall	F1-score
First author	0.65	0.69	0.66
Collaborators	0.50	0.28	0.35

4.3 Match-Log Reconstruction Accuracy

Tables 2 and 3 show the reconstruction accuracy of hand-related events. For hand-registration events, the F1-score was 0.70 for the author’s viewpoint and 0.47 for the collaborator viewpoint. For hand-usage events, the F1-score was 0.66 for the author’s viewpoint and 0.35 for the collaborator viewpoint. These results indicate that hand-related events could be partially reconstructed, but performance decreased for collaborator footage. Hand-usage events were especially difficult because card disappearance may reflect actual use, temporary occlusion, or movement outside the frame.

For play-area reconstruction, the F1-score for Pokémon placement changes was 0.61, and Energy attachment accuracy was 0.76. These results suggest that major play-area changes can be reconstructed to some extent, although errors occurred when cards were close together, the play area became crowded, or hand and play-area changes could not be aligned accurately.

4.4 Exploratory Use in Post-Game Discussion

In this separate exploratory observation, we examined how three pairs of players referenced reconstructed match logs during post-game discussion. Each pair played two matches. After one match, they conducted a memory-based post-game discussion without using any external record. After the other match, they conducted a log-supported post-game discussion using the log.

Because this observation involved only three pairs and was not fully controlled, we report descriptive tendencies rather than statistical effects. On average, discussion time increased from 6.3 minutes in the memory-based condition to 15.3 minutes in the log-supported condition. This difference may reflect a change in how players revisited the match, rather than an improvement in reflection quality, and may also include redundancy.

Log-supported discussions also referred more often to information that was difficult to reconstruct from memory alone. References to hand information increased from 1.0 to 6.3 times per discussion on average. Players used the logs to locate specific moments, confirm play-area changes, and reconsider alternative actions based on the available cards.

These observations should be interpreted as exploratory findings from a small observational study, rather than as evidence of improved learning outcomes or reflection quality. Overall, they suggest that reconstructed logs may help players revisit private hand information and the available options at the time of each action, not only the visible result.

5 Discussion

5.1 Feasibility of Partial Match Reconstruction

The main finding of this study is not simply that cards can be detected from video, but that different types of match information have different levels of reconstructability in ordinary in-person CCG play. The evaluation results indicate that chest-mounted smartphone footage can provide useful information for partially reconstructing hand and play-area changes. In particular, the relatively high detection accuracy for hand cards and play-area cards suggests that a lightweight recording setup can capture information useful for reviewing available options and resulting play-area changes.

However, the reconstructed logs remained incomplete, especially for hand-related events and crowded play areas. These findings clarify which information can serve as reflection cues and what support is needed for reliable match-log generation. Therefore, the generated match log should be treated not as a complete game-state record, but as a reflection-oriented record of observable hand and play-area changes in practice.

5.2 Implications for Post-Game Discussion

The exploratory observations suggest that the value of reconstructed match logs lies not in providing a complete replay, but in offering a shared reference for discussion. By presenting hand information and play-area changes together, the logs can help players revisit what options were available, what actions were taken, and how the play-area state changed.

However, this study does not claim that the generated match logs improve learning outcomes or the quality of post-game reflection. The purpose of the exploratory observations was to examine how players used reconstructed logs during discussion, not to evaluate the effectiveness of reflection itself. Therefore, the current logs should be treated as discussion cues rather than authoritative records of the match or automated explanations of player decisions.

This distinction is important for positioning the study. The proposed approach does not infer why players made decisions, nor does it analyze their emotions, speech, or internal thought processes. Instead, this study focuses on recording observable game-state information that can serve as a shared reference during post-game discussion. In this sense, match reconstruction can provide material for reflection by helping players revisit concrete events and state changes without relying only on memory.

5.3 Limitations and Future Work

This study has several limitations. First, the proposed method does not completely reconstruct the entire game state. Chest-mounted camera footage is affected by occlusion, partial visibility, camera angle, posture, and hand movements, which caused some cards and events to be missed or incorrectly registered. Future systems should support stable recording through camera-positioning guidelines, simple calibration, and feedback when cards move outside the field of view.

Second, the evaluation was limited in scale. The quantitative evaluation used 15 Pokémon TCG matches played by the first author and five collaborators, and the target card set was limited to 18 types. Although this setting was useful for a preliminary evaluation, the results may depend on the decks, players, recording conditions, and card layouts used in the study. Future evaluations should include more players, more diverse decks, and different play environments to examine the generalizability of the proposed method.

Third, this study did not record or analyze players' emotions, speech, or facial expressions. These factors may be important for understanding decision-making and communication during post-game discussion. However, the purpose of this study is to establish a basis for recording observable game-state information in ordinary in-person paper-card play. Future work should combine reconstructed match logs with audio recordings, interviews, and conversation analysis to examine how game-state records and player interactions relate to post-game reflection.

Finally, the evaluation of match-log use in post-game discussion was preliminary and does not demonstrate learning effects or improvements in reflection quality. Future studies should compare memory-based and log-supported discussions with more participants, using measures such as revisited events, references to hand information, discussion balance, and perceived usefulness to clarify how reconstructed logs support strategic reflection in in-person CCGs.

6 Conclusion

This study explored a lightweight approach for reconstructing in-person CCG matches using chest-mounted smartphone cameras. Rather than aiming for complete game-state reconstruction or evaluating the effectiveness of post-game reflection, this study examined whether observable hand and play-area information could be organized into a reviewable match log. Through an evaluation using match footage, we showed that hand cards and play-area cards can be detected with relatively high accuracy, and that some hand-related events and play-area changes can be partially reconstructed. At the same time, the results revealed practical challenges, including camera angle, player posture, occlusion, and incomplete event reconstruction. Future work will improve match-log robustness and examine how reconstructed logs can support post-game discussion.

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