Dual Eye Tracking as a Tool to Assess Collaboration

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Abstract. In working towards unraveling the mechanisms of productive collaborative learning, dual eye tracking, a method where two people's eyes are tracked as they collaborate on a task, is a potentially helpful tool to identify moments when students are collaborating effectively. However, we are only beginning to understand how eye gaze relates to effective collaborative learning and how it fits in with other data streams. In this paper, we present three broad areas of analysis where we believe dual eye tracking will promote our understanding of collaborative learning. These areas are: (a) How eye gaze is associated with other communication measures, (b) how eye gaze is associated with task features, and (c) how eye gaze relates to learning outcomes. We present exploratory analyses in each of the three areas using a dataset of 28 4th and 5th grade dyads working on an Intelligent Tutoring System for fractions. Our analyses illustrate how dual eye tracking could be used in conjunction with other data streams to assess collaborative learning.

Keywords: collaborative learning, intelligent tutoring system, dual eye tracking

1 Introduction

Collaboration can be an effective tool for learning; however, it can be difficult to identify the mechanisms of collaboration and how students' actions may lead to learning when working in a group. The communication between partners plays a large role in the success of the group [3], and there are many different processes that happen during a collaborative session that can affect learning such as speech, joint attention, and tutor feedback. By analyzing these different processes separately and together, we may be able to develop a better understanding of the collaborative learning process. In this paper, we specifically focus on dual eye tracking, a method where two people's eyes are tracked as they collaborate on a task, with an Intelligent Tutoring System (ITS) and explore how it could be used with other data streams to analyze students' collaborative interactions. By using multiple data streams that include eye gaze, we may be able to have insights into collaboration that were not otherwise possible.

Research shows eye gaze is tied to communication, making eye tracking a promising method to use for the analysis of collaborative learning [9]. Previous research has shown that there is a link between eye gaze and speech [4], [9]. When people hear a reference through speech, their eye gaze will follow that object [9], and when people are describing a picture, their eye gaze will look at the relevant part of the picture before it is described [4]. These studies show a link between speech and eye gaze that goes in both directions. This same pattern follows when people are working on a task together. There is a coupling of the collaborators' eye gaze around a reference [12]. The eye gaze has a closer coupling when each of the collaborators has the same initial information and when there is a shared selection [7], [12], suggesting that task features influence eye gaze. The coupling of eye gaze between collaborating partners may be an indicator of quality interaction and better comprehension [6], [11]. It also may be associated with better learning because there is more comprehension and understanding from the interactions with a closer coupling of eye gaze. Much of the previous work has focused on the correlation of eye gaze with speech, but it is still an open question of how dual eye tracking can be used to assess the effectiveness of collaboration in terms of learning and how it is associated with other process data, especially within an ITS.

In this paper, we will explore three types of broad questions that can be answered by using dual eye tracking: (a) How is eye gaze associated with other communication measures, (b) how is eye gaze associated with task features, and (c) how is eye gaze associated with learning outcomes. By answering these questions we may have a better understanding of how the interface of an ITS relates to both speech and the learning process while students are collaborating. There are multiple measures that can be gathered through dual eye tracking to understand eye gaze. In this paper, we will focus on one such measure, joint attention, which measures the relative amount of time two students are looking at the same area at the same time and corresponds to a very close coupling of eye gaze. Using a dataset of 4th and 5th grade students working on a fractions ITS, we explore a specific question in each of these three broad areas. These exploratory analyses demonstrate the potential of questions involving dual eye tracking and other data streams to be used to analyze collaborative learning.

2 Methods

2.1 Experimental Design and Procedure

Our data set involves 14 4th and 14 5th grade dyads from a larger study [10]. The dyads were engaged in a problem-solving activity in a collaborative ITS for fractions learning while communicating through audio only using Skype. Each dyad worked with the tutor for 45 minutes in a lab setting at their school. The morning before working with the tutor and the morning after working with the tutor, students were given 25 minutes to complete a pretest or posttest individually on the computer to assess their learning. Through the lab set-up in the school, we were able to collect dual eye tracking data, transcript data, and tutor log data in addition to the pretest and posttest measures for multiple stream of data.

2.2 Tutor Design

The ITS was developed using Cognitive Tutoring Authoring Tools and consisted of two problem sets, targeting procedural and conceptual knowledge. The tutor provides standard ITS support, such as hints and feedback [14], combined with embedded collaboration scripts. Each student had their own view of the collaborative tutor that allowed the students to have a shared problem space and synchronously work while being able to see slightly different information and to take different actions. Three different features supported the student collaboration. On some tutor steps, the students were *assigned roles* where they were either responsible for entering the answer or for asking questions of their partner and providing help with the answer. We supported other problem steps through *individual information* [13]. Here the students were each provided with a different piece of information that they needed to share with their partner. The final feature that was used to support collaboration was *cognitive group awareness* [5]. This feature was implemented in the tutor by providing each student an opportunity to answer a question individually before seeing each other's answers and being asked to provide a consensus answer.

2.3 Data and Dependent Measures

A computer-based test was developed to closely match the target knowledge covered in the tutors. The test comprised of 5 procedural and 6 conceptual test items, based on pilot studies with similar materials. Two isomorphic sets of questions were developed, and there were no differences in performance on the test forms, $t(79) = 0.96$, $p = 0.34$. The presentation of these forms as pretests and posttests was counterbalanced.

In addition, to pretest and posttest measures, we also collected process data including tutor log data, transcript data, and dual eye tracking data. The log data consisted of the transactions that the students took with the ITS. These include attempts at solving each step together with the request of hints and errors.

We coded the dialogue transcript data using a rating scheme with four categories: interactive dialogue, constructive dialogue, constructive monologue, and other. For our analysis, we focused on the interactive dialogue, in which students engage in actions such as co-construction and sequential construction. Interactive dialogue aligns with ICAP's joint dialogue pattern [2]. Our rating scheme was developed to look at groups of utterances associated with subgoals (i.e., a group of steps that all are for the same goal) to account for the interactions between the students. An inter-rater reliability analysis was performed to determine consistency among raters (Kappa= 0.72).

In addition to collecting log data and transcript data, we also collected dual eye tracking data using two SMI Red 250 Hz infrared eye tracking cameras. We calculated a measure of joint attention through gaze recurrence [1], [8]. Gaze recurrence is the proportion of times where the fixations are at the same location for each student. To calculate the joint attention from the gaze data, we used gaze recurrence with a distance threshold of 100 pixels to approximate the percentage of time that students were looking at the same thing at the same time. This distance threshold was chosen to align with prior research [6] and is close to the size of the interface elements.

3 Research Questions and Analysis

The first broad area of analysis is how eye gaze is associated with other communication measures. Within this area, we investigated how joint attention differs between subgoals without talk and subgoals with talk. We also explored whether or not there is an interaction with the subgoals that have errors. Based on previous work, we hypothesize that subgoals with talk will have a higher level of joint attention than subgoals with no talk since talk has been found to be coupled with eye gaze and speech might guide the visual attention [9]. In addition, we hypothesize that subgoals where an error occurred will have a higher level of joint attention compared to subgoals where no error occurred because there will be a visual red mark on the screen for the students to discuss [12]. To investigate the association between talk and joint attention, we used a hierarchical linear model with two nested levels to analyze how the talk during subgoals related to the joint attention. At level 1, we modeled if talk occurred and if one or more errors occurred for the subgoals. At level 2, we accounted for random dyad differences. We found no effect of errors on joint attention, so it was removed from the model. We found greater joint attention for subgoals that had talk ($M = 0.25$, $SD = 0.13$) versus those that did not ($M = 0.22$, $SD = 0.14$), $t(1705)= 12.66$, $p < .001$, showing a coupling between talk and joint attention that extends previous results to younger learners working in an ITS environment.

The second broad area of analysis is how eye gaze is associated with task features. For this area, we investigated how eye gaze is associated with the tutor's three types of collaboration support. Based on previous work, we hypothesize that subgoals supported through individual information would have the lowest joint attention since there is no joint reference for the students on the screen [7]. To investigate the association between collaboration features and joint attention, a hierarchical linear model with two nested levels was used to analyze how collaboration features relate to the joint attention. At level 1, we modeled the type of collaboration support of the subgoals along with the talk type to control for this covariate. At level 2, we accounted for random dyad differences. We found that the joint attention for subgoals that were supported through cognitive group awareness ($M = 0.19$, $SD = 0.11$) was lower than that for subgoals supported through roles ($M = 0.25$, $SD = 0.14$), $t(1705)= -4.19$, $p < .001$, indicating that task type has an impact on joint attention.

The third broad area of analysis is how eye gaze is associated with learning. Within this area, we investigated how joint attention correlates with learning gains for conceptual and procedural knowledge. Based on previous work where we analyzed the first four questions (opposed to the entire session) [1], we hypothesize that joint attention will be correlated with conceptual learning gains, but not procedural learning gains, because a deeper understanding is needed to acquire the conceptual information that can be supported through joint attention [11]. To investigate this question, we computed a linear regression between posttest score and joint attention while controlling for pretest scores. Individual pretest and posttest scores were averaged for each member of the dyad for a single score for each dyad, and the joint attention was calculated for each dyad for the entire 45-minute session. Our results replicate previous findings, where for the conceptual condition, there were no significant results for conceptual or procedural posttest scores. For the procedural condition, there was no significance for procedural posttest scores, but joint attention significantly predicts conceptual posttest scores when controlling for conceptual pretest score, $t(10) = 2.6$, $p = 0.03$, showing joint attention may be more important for gaining conceptual knowledge on procedural problems, whereas students working on the conceptual problems were able to learn the same information with less joint attention.

4 Discussion

Although the correspondence of eye gaze with speech has been studied before, it is still an open question of how dual eye tracking can be used to assess the effectiveness of collaboration in terms of learning and how it is associated with other process data. In this paper, we explore the importance of eye gaze for collaborative learning analysis by presenting three different areas of analysis for using dual eye tracking data. Although the results are preliminary, these questions provide a broad structure and illustrate the potential of dual eye tracking to be used with other data streams.

Can dual eye tracking be used to understand the collaborative learning process? Through our analysis, we found that subgoals where talk occurs have a higher level of joint attention, extending previous results to younger learners and an ITS environment [12]. This result indicates that in an environment where there is step-by-step guidance and steps are revealed one at a time, which may guide eye gaze, there is still a benefit of speech for referencing items on the screen. Although we did not find any impact of errors on joint attention, analyzing the joint attention immediately after an error may provide a better indication of the effect of errors on joint attention. In addition, we found that subgoals supported through cognitive group awareness had a lower level of joint attention compared to those supported through roles showing the importance of the task features on collaboration. The difference between collaborative features on joint attention may be because the students would be looking at different points while answering individually and would then be looking at their partner's answer after it is revealed on cognitive group awareness, which may split the attention of the partners. We also used dual eye tracking to identify moments where collaboration may successfully support learning. We found joint attention as a significant predictor of conceptual posttest scores in the procedural condition, showing collaboration and joint attention may be important for conceptual knowledge specifically when it is not being directly supported. Although the results are preliminary, they show the potential of using dual eye tracking along with other data streams to better understand collaboration. For collaborative learning, dual eye tracking can provide insights into tasks that elicit collaboration as well as providing insights into how joint eye gaze interacts with other communication measures to impact learning.

For future work, we would like to expand the three areas of analysis around dual eye tracking beyond joint attention. There are other measures such as AOIs (areas of interest) analyses and gaze patterns that would be of interest in each of the three areas and can be measured through dual eye tracking. These different measures of eye gaze would not only provide additional ways of comparing collaboration within groups by looking at AOIs and gaze patterns that occur for partners at the same time, but would also allow the comparison to students working individually to see how collaboration affects the learning process. In addition, in our analyses so far, we have analyzed joint attention at the subgoal level and the dyad level, but analysis at additional grain sizes, such as a few seconds around errors and the problem level, would allow us to ask a wider range of questions. This future work will build upon the analysis presented in this paper to further explore the three broad areas of analysis for dual eye tracking to shed light on the mechanisms of collaborative learning.

Acknowledgments. We thank the CTAT team, Daniel Belenky, and Amos Glenn for their help. This work was supported by Graduate Training Grant # R305B090023 and by Award # R305A120734 both from the US Department of Education (IES).

5 References

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