Pre-publication version of:
Olsen, J., Aleven, V., & Rummel, N. (2017). Exploring dual eye tracking as a tool to assess collaboration. In P. Kyllonen, A. von Davier, & M. Zhu (Eds.), *Innovative Assessment of Collaboration* (pp. 157-172). New York: Springer.

Exploring 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 is a potentially helpful methodology. Dual eye tracking is a method where eye-tracking data from people working on a task are analyzed jointly, for example to extract measures of joint visual attention. We explore how eye gaze relates to effective collaborative learning and how analysis of dual eye-tracking data might enhance analysis of other data streams. In this chapter, we identify three broad areas of analysis where dual eye tracking may enhance understanding of collaborative learning processes: (a) how eye gaze is associated with other communication measures, (b) how eye gaze is associated with features of the task environment, and (c) how eye gaze relates to learning outcomes. We present analyses in each of the three areas through joint visual attention, using a dataset of 28 4th and 5th grade dyads working on an Intelligent Tutoring System for fractions. By combining eye tracking, dialogue transcripts, tutor logs, and pre/post data, we show the potential of using dual eye tracking to better understand the collaborative learning process.

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

Introduction

Collaboration can be an effective way of learning; however, it is challenging to identify mechanisms of productive collaboration and to ascertain how students' actions lead to learning when working in a group. The communication between partners is likely to play a large role in the success of the group (Chi & Wylie, 2014), and there are many different processes that happen during a collaborative session that can affect learning such as speech, joint visual 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 chapter, we focus on dual eye tracking, a method where eye-tracking data from collaborating partners are gathered and are analyzed jointly, to investigate if eye movement data reveal information about collaboration that may not be readily apparent in other data streams (Jermann, Mullins, Nüssli, & Dillenbourg, 2011; Richardson & Dale, 2005). We focus on learning with an Intelligent Tutoring System (ITS) for 4th and 5th grade fractions learning that supports learning collaboratively, which is atypical of ITSs (Olsen, Belenky, Aleven, & Rummel, 2014). We explore how dual eye tracking data 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 gain insights into collaboration that would not otherwise be possible.

Research shows eye gaze is tied to communication, making eye tracking a promising method to use for the analysis of collaborative learning (Meyer, Sleiderink, & Levelt, 1998). Previous research has shown that there is a link between eye gaze and speech (Griffin & Bock, 2000; Meyer, Sleiderink, & Levelt, 1998). When people hear a reference through speech, their eye gaze is likely to follow the referenced object (Meyer, Sleiderink, & Levelt, 1998). Similarly, when people describe a picture, their eye gaze is likely to fixate on a relevant part of the picture before they describe it (Griffin & Bock, 2000). These studies show a link between speech and eye gaze that goes in both directions: eye gaze can precede the mention of an object or follow it. This same pattern occurs when people work on a task together. There is a coupling of the collaborators' eye gaze around a reference (Richardson, Dale, & Kirkham, 2007), meaning that the collaborators' gaze may fixate, at approximately the same point in time, at the object referenced in the dialogue, for example just before mentioning it and just after hearing about it. The eye gaze has a closer coupling when each of the collaborators has the same initial information and when collaborators can visually share important objects that they are referencing in speech (Jermann & Nüssli, 2012; Richardson, Dale, & Kirkham, 2007), suggesting that task features influence eye gaze. The coupling of eye gaze between collaborating partners may be an indicator of interaction quality and comprehension (Jermann, Mullins, Nüssli, & Dillenbourg, 2011; Richardson & Dale, 2005). It also may be associated with better learning, assuming there is more comprehension and understanding from interactions with a closer coupling of eye gaze. In addition to using eye tracking as an analysis tool, eye tracking has also been used within the learning environment to signal to collaborating partners what each is looking at (Schneider & Pea, 2013). When using eye tracking as an analysis tool, 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 chapter, we 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? (c) How is eye gaze associated with learning outcomes? In our work, we have looked at how these three questions can be answered when students are working with an ITS. Learning with an ITS when working individually has been shown to be very successful, especially within mathematics (Ritter et al., 2007; Rau et al., 2012). In our ITS, we support collaboration through an embedded collaboration script and are able to study collaboration through the collection of log data, transcript data, dual eye tracking data, and pre/posttest data. By answering these questions we may have a better understanding of how the different features of the learning process relate and have an impact on learning for students collaborating. There are multiple measures that can be gathered through dual eye tracking to understand eye gaze during collaboration. In this chapter, we focus on one such measure, joint visual attention, which measures the coupling of eye gaze as the relative amount of time two collaborating students look at the same area at the same time. Using a dataset of 4th and 5th grade students working on an ITS for fractions learning, we explore a specific question in each of these three broad areas. These exploratory analyses demonstrate the potential of combining dual eye tracking and other data streams to analyze collaborative learning.

Methods

Experimental Design and Procedure

Our data set involves 14 4th and 14 5th grade dyads from a larger study in which we tested a hypothesis about differential benefits of collaborative versus individual learning (Olsen, Belenky, Aleven, & Rummel, 2014). The current chapter focuses not on that hypothesis but on the use of dual eye tracking in collaborative learning research. The dyads were engaged in a problem-solving activity using a networked collaborative ITS while communicating through only audio using Skype in a between-subjects design. Each teacher paired the students participating in the study based on students who would work well together and had similar, but not equivalent, math abilities. The pairs were then randomly assigned to either work collaboratively or individually and on either a procedurally-oriented or a conceptually-oriented problem set. (In this chapter, we present data from the dyads only.) 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. Although the lab was set-up in the school, we were able to collect dual eye tracking data, dialogue data, and tutor log data in addition to the pretest and posttest measures.

Tutor Design

The dyads in our study used a tutoring system for fractions learning that we developed using the Cognitive Tutoring Authoring Tools (Aleven, McLaren, Sewall, & Koedinger, 2009; Aleven et al., 2016; Olsen et al., 2014). This tutor consisted of two problem sets, one targeting procedural knowledge and one targeting conceptual knowledge about fraction equivalence. Procedural knowledge is the knowledge about the steps needed to solve a problem and the ability to execute these steps in the correct order (Rittle-Johnson, Siegler, & Alibali, 2001). Conceptual knowledge is the knowledge of how the different elements of the domain are interrelated (Rittle-Johnson, Siegler, & Alibali, 2001). Each dyad in the study worked on only one of these two problem sets, given the study goals mentioned above. Within each problem, the tutor provided standard ITS support, such as prompts for steps, next-step hints, and step-level feedback that allows the problem to adapt to the student's problem-solving strategy (VanLehn, 2011), For the collaboration, the ITS support mentioned above was combined with embedded collaboration scripts. Each subgoal, a group of related steps (e.g., finding the factors of 9), in the problem is revealed one at a time. Each student had their own view of the collaborative tutor on separate computers 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.

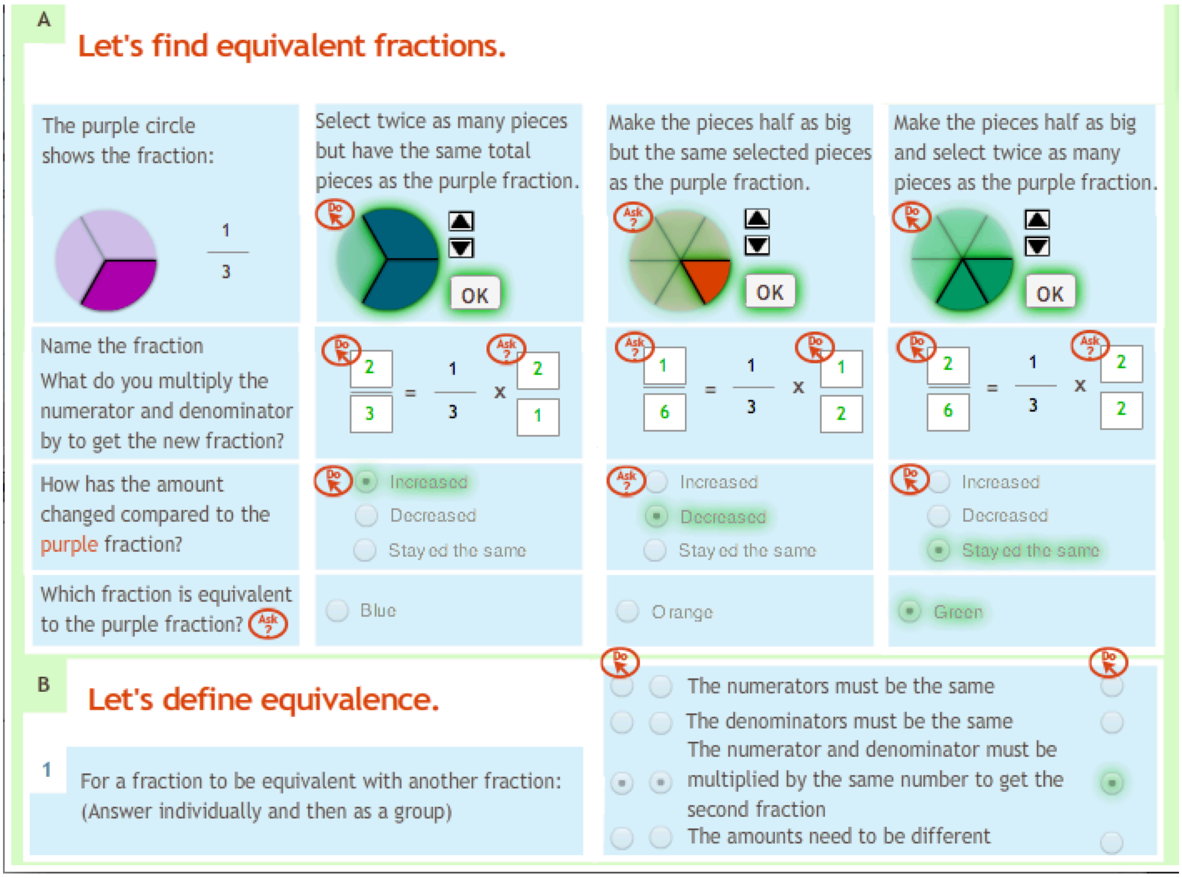

Figure 1. For the display of a single student, section A shows an example of roles for each subgoal of the problem where the "Do" icon indicates the student is responsible for entering the answer while the "Ask" icon indicates the student is responsible for asking questions and helping to find the correct answer. Section B shows an example of cognitive group awareness.

In addition to providing step-level guidance to students within each problem, the tutor was designed to support effective collaboration between students in three different ways. First, for many steps, the students were assigned *roles* (see Figure 1), which has been shown to be an effective collaboration scripting feature (King, 1999). Roles support collaboration by assigning students certain tasks within the given problem. This provides the students with guidance for their own responsibilities and with an understanding of their partner's responsibilities. In our tutors, on steps with roles, one student was responsible for entering the answer and the other was responsible for asking questions of their partner and providing help with the answer. The tutor indicated the current role for the students through the use of icons on the screen (see Figure 1). A second way in collaboration was supported was by providing students with information they were responsible for sharing with their partner, *individual information* (Slavin, 1996). The students were each provided with a different piece of information needed for the solution to the problem; thus they needed to share this information with their partner as indicated by a "share" icon (see Figure 2). The final feature that was used to support collaboration was *cognitive group awareness,* where knowledge that each student has in the group is made known to the group (Janssen & Bodemer, 2013). This feature was implemented on steps where the students needed to extract a pattern from the earlier steps in the problem. Each student was given an opportunity to answer a question individually before the students were shown each other's answers and asked to provide a consensus answer (see Figure 1).

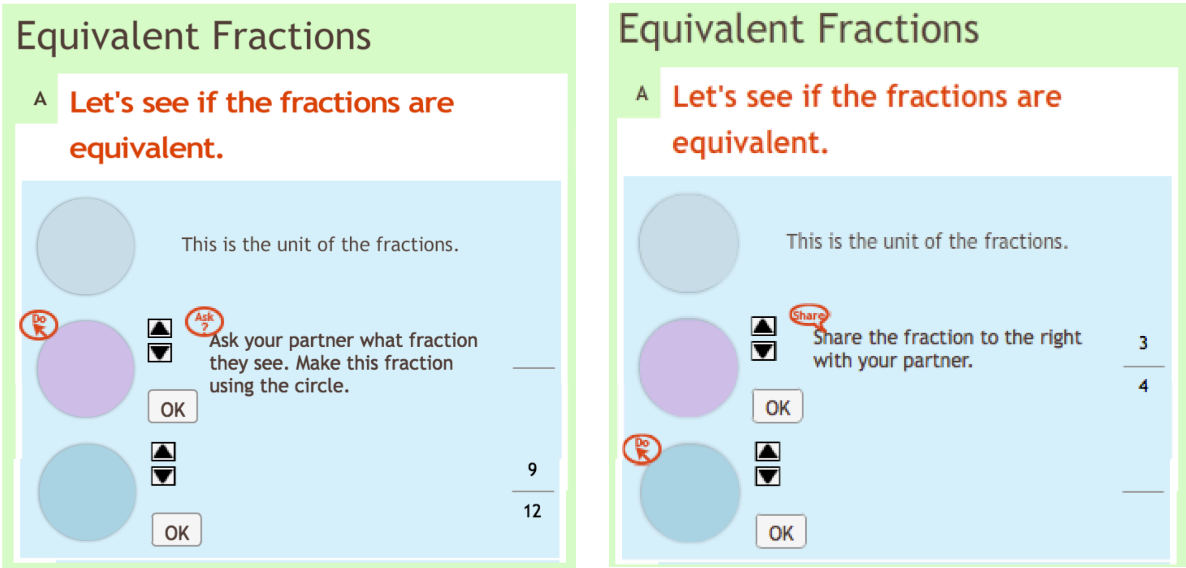

Figure 2. An example of individual information where student A (left) is responsible for making the fraction that their partner, student B, (right) has in symbolic form and must share.

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. Between pretest ($M = 2.06$, $SD = 1.25$) and posttest ($M = 2.56$, $SD = 1.05$) for conceptual knowledge, there were significant learning gains, $F(1, 25) = 7.66$, $p = .010$, but there were no learning gains on procedural knowledge from pretest ($M = .70$, $SD = .77$) to post-test ($M = .87$, $SD = .84$), $F(1, 25) = 1.13$, $p = .296$ (Belenky, Ringenberg, Olsen, Aleven, & Rummel, 2014).

In addition, to pretest and posttest measures, we also collected process data including dual eye-tracking data, tutor log data, and dialogue data. We collected eye-tracking data using two SMI Red 250 Hz infrared eye-tracking cameras. We recorded each student's eye movement separately, synchronized the eye-tracking logs of the students in each dyad, and analyzed the fixation data of the students in a dyad jointly. We calculated a measure of joint visual attention through gaze recurrence (Belenky, Ringenberg, Olsen, Aleven, & Rummel, 2014; Marwan, Romano, Thiel, & Kurths, 2007). Gaze recurrence is the proportion of times that collaborating students fixate their gaze simultaneously at the same location. In other words, it is the proportion of time that the students' eye gazes are coupled. To calculate the joint visual 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 (Jermann, Mullins, Nüssli, & Dillenbourg, 2011) and is close to the size of many of the interface elements.

The log data captured the time-stamped transactions that the students took with the ITS. These include attempts at solving each step and their request for hints; the log data also includes the tutor's responses, including whether attempts at solving were correct, what knowledge components they involved, and what errors were made, as well as any hint and feedback messages that the tutor presented to the students.

We transcribed the students' dialogues and coded the transcript data using a rating scheme with four categories: interactive dialogue, constructive dialogue, constructive monologue, and other. We developed this rating scheme to align with the ICAP framework (Chi, 2009) and to distinguish between the different types of talk ranked on how conducive we hypothesize they would be for learning. For our analysis, we focused on the interactive dialogue, which aligns with ICAP's joint dialogue pattern (Chi, 2009) and is hypothesized to be more conducive to learning than other types of talk and dialogue. In interactive dialogue, students engage in actions such as sequential construction and co-construction. In sequential construction, each student allows their partner to finish their turn before adding additional information, while in co-construction, students do not wait for their partner's turn to finish but instead finish their partner's thought. Our rating scheme was developed to look at utterances associated with each subgoal (i.e., a group of related steps within a tutor problem) to account for the interactions between the students. An inter-rater reliability analysis was performed to determine consistency among raters (Kappa= 0.72).

Table 1. Rating scheme categories defined and its mapping to the ICAP framework.

Type of Talk	Overt Actions	ICAP Framework
Interactive Dialogue	Discussing an answer, co-construction, soliciting a request for help or confirmation of agreement	Joint Dialogue
Constructive Dialogue	Guessing as a group, argumentation without explanation, agreeing with partner without adding on	Individual Dialogue
Constructive Monologue	Self explanation	Individual Dialogue
Other	Telling the answer, work coordination, active reading, and off topic talk	

Research Questions and Analysis

We now illustrate how we used dual eye tracking data, in conjunction with other data sources, to study collaborative learning processes and their relations with learning. We focus on each of our three questions in turn.

Relation between eye gaze and dialogue

The first broad area of analysis is how eye gaze is associated with other communication measures, specifically, our coding of the dialogue data. By understanding the association between eye gaze and other measures of communication, we may begin to understand how eye gaze and dialogue interrelate, as well as where dual eye tracking might provide information about the collaboration that dialogue data does not reveal. Specifically, we investigated how joint visual attention differs between subgoals without talk and subgoals with talk. Based on previous work, we hypothesize that subgoals with talk will have a higher level of joint visual attention than subgoals with no talk. As mentioned, research has shown that talk is coupled with eye gaze; in particular, speech can guide visual attention (Meyer, Sleiderink, & Levelt, 1998).

We extend these prior analyses by asking whether relations between eye gaze and dialogue vary depending on what happens at the problem-solving level, namely, whether students commit problem-solving errors or solve steps correctly, as indicated by tutor feedback. As mentioned, when students enter their attempts at solving a step into the tutor interface, the software responds by providing color-coded correctness feedback, with green indicating correct answers and red indicating incorrect answers. Because errors are often viewed as learning opportunities (Ohlsson, 1996), it is interesting to ask whether in collaborative learning scenarios, they tend to be moments of particularly intense collaboration. Suggestive of that notion, in our data set, we found that subgoals with errors have higher frequency of talk (Olsen, Rummel, & Aleven, 2015). Here we ask whether errors may show interesting relations with eye gaze and whether errors modify the relation between eye gaze and dialogue measures. Not only do errors have a clear visual manifestation on the screen as they serve as an external record of the last step entered, made especially salient by the tutor's red feedback, but also as students discuss the error, their eye gaze may fixate on the object of discussion (i.e., the error) (Richardson, Dale, & Kirkham, 2007). Therefore, we hypothesize that subgoals on which an error occurred will have a higher level of joint visual attention than subgoals where no error occurred.

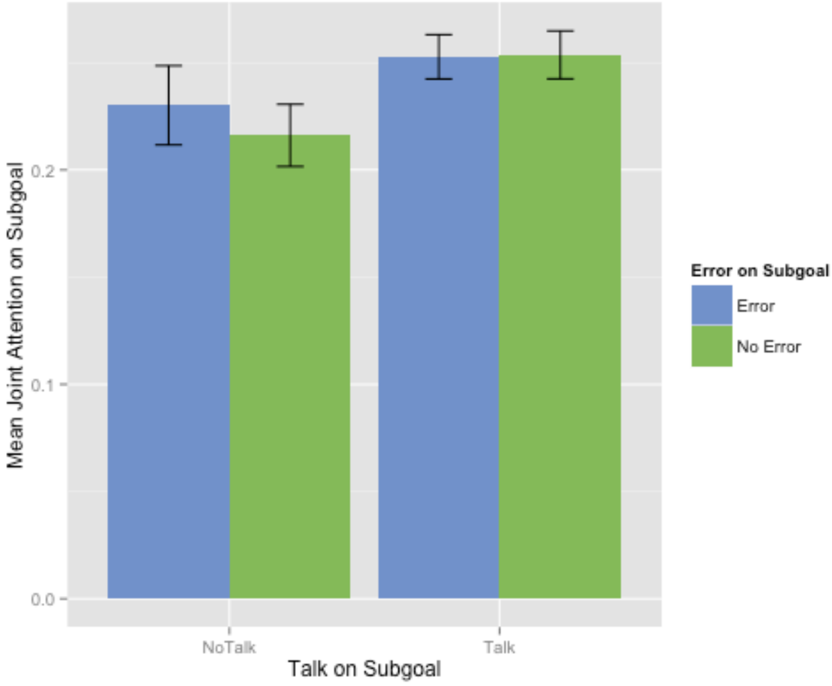

Figure 3. Joint visual attention (with standard errors) as a function of whether there was talk on the given subgoal and whether there were errors on the given subgoal

To address these hypotheses, we investigated how joint visual attention differs between subgoals with talk and subgoals without talk. We also explored whether or not there is an interaction between errors and talk, regarding the level of visual attention, such that the greatest level of joint visual attention is found for subgoals with talk and errors (see Figure 3). We used a hierarchical linear model with two nested levels to analyze how the talk during subgoals related to the joint visual attention as our dependent variable. At level 1, we modeled if talk occurred and if one or more errors occurred for the subgoals as our independent variables. At level 2, we accounted for random dyad differences. We found no effect of errors on joint visual attention, so we removed the error variable from the model as an independent variable. We found greater joint visual attention for subgoals that had talk ($M = 0.25$, $SD = 0.13$) versus those that did not ($M = 0.22$, $SD = 0.14$, $t(1705)= 2.66$, $p < .001$), $\omega^2 = 0.06$, showing a coupling between talk and joint visual attention that extends previous results to younger learners working in an ITS environment. However, we did not find support for our hypothesis that the presence of errors has an impact on joint visual attention.

Relation between eye gaze and tutor support for collaboration

The second broad area of analysis is how eye gaze is associated with features of the task environment, in our case, the design of the tutor interface to support collaboration. The tutor provided a different interface for different problem types, since the interface is designed to make the steps of the problems explicit for the students. Cutting across these different interfaces, however, are the three tutor features that support collaboration, described above (roles, individual information, and cognitive group awareness). We focus on these collaborative features and how they might affect joint eye gaze measures. By analyzing the association between eye gaze and different task features, we can begin to understand the impact that task features can have at the process level beyond what can be abstracted from student dialogue. As well, this investigation reveals to what degree the support for collaboration provided by the tutor manifests itself in joint visual attention. Based on previous work, we hypothesize that subgoals supported through individual information would have the lowest joint visual attention, compared to subgoals with the two other collaborative features, since there is no joint reference for the students on the screen (Jermann & Nüssli, 2012). We did not have an expectation for whether the cognitive awareness feature and the roles feature would lead to differences in joint visual attention.

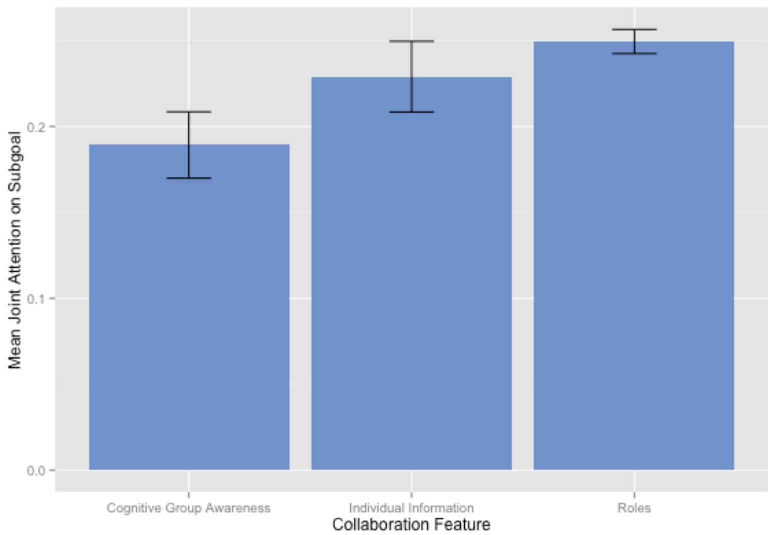

Figure 4. Joint visual attention (with standard errors), as function of the collaborative features present

To investigate the association between collaboration features and joint visual attention, a hierarchical linear model with two nested levels was used to analyze how collaboration features relate to the joint visual attention as the dependent variable. At level 1, we modeled the type of collaboration support of the subgoals along with the talk type to control for this covariate as the independent variables. At level 2, we accounted for random dyad differences. We found that the joint visual 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 ($M = 0.25$, $SD = 0.14$), $t(1705) = -4.19$, $p < .001$, $\omega^2 = 0.10$, indicating that how the task environment of supports collaboration seems to have an impact on joint visual attention (see Figure 4). These results do not support our hypothesis that individual information would have the lowest joint visual attention.

Relation between eye gaze and learning outcomes

The third broad area of analysis is how eye gaze is associated with learning gains. Within this area, we investigated how joint visual attention correlates with learning gains for conceptual and procedural knowledge as measured by pretest and posttest. Our initial hypothesis was that joint visual attention would be associated with greater learning gains, more strongly so for students working with conceptually-based problems. This hypothesis tests the intuition that if joint eye gaze is an indicator of productive collaborative learning processes, then it should correlate with the learning outcomes of these processes. This notion finds some support in earlier research that found a positive relation between understanding and joint eye gaze (Richardson & Dale, 2005). However, this work does not distinguish between the types of knowledge that are being acquired. Our hypothesis takes into account the types of knowledge the students are targeting and is informed by prior work that found that collaboration can be more beneficial for learning conceptual knowledge than procedural knowledge (Mullins, Rummel, & Spada, 2011). Therefore, we predict the correlation between joint eye gaze and conceptual learning gains to be stronger than that between eye gaze and procedural learning.

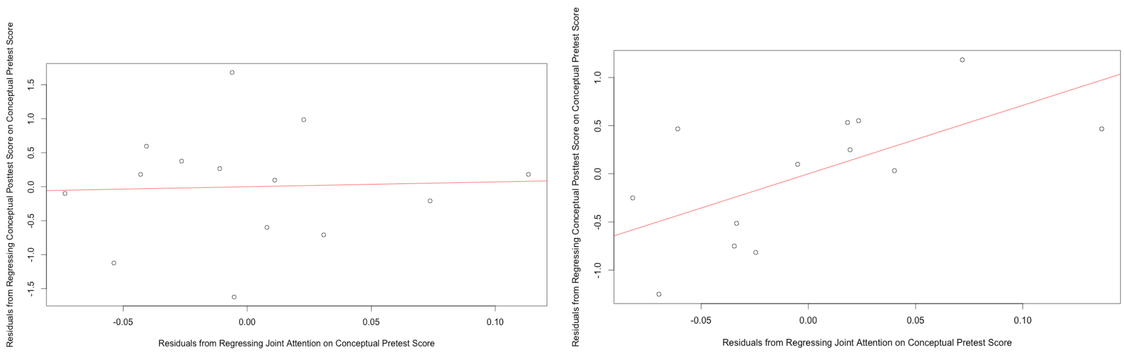

Figure 5. Partial correlation of joint visual attention with posttest scores on conceptual knowledge for students in the conceptual condition (left) and the procedural condition (right)

To investigate this question, we computed a hierarchical linear model with two nested levels to analyze how posttest scores (dependent variable) correlated to the joint visual attention as the independent variable while controlling for the pretest score as a covariate. At level 1, we modeled the joint visual attention and the pretest scores. At level 2, we accounted for random dyad differences. The joint visual attention was calculated for each dyad for the entire 45-minute session. We found, as hypothesized, that joint visual attention significantly predicts conceptual posttest scores when controlling for conceptual pretest score. However, contrary to our expectations, this effect was confined to the students in the procedural condition, $t(11) = 2.3$, $p = 0.04$, $\omega^2 = 0.57$ (see Figure 5). Recall that these students solved problems targeting procedural knowledge of fractions only. There was no significant correlation between procedural learning and joint eye gaze (see Figure 6). These results thus provide partial support for our hypothesis. We note that these results are consistent with preliminary findings based on a subset of the data (Belenky, Ringenberg, Olsen, Aleven, & Rummel, 2014).

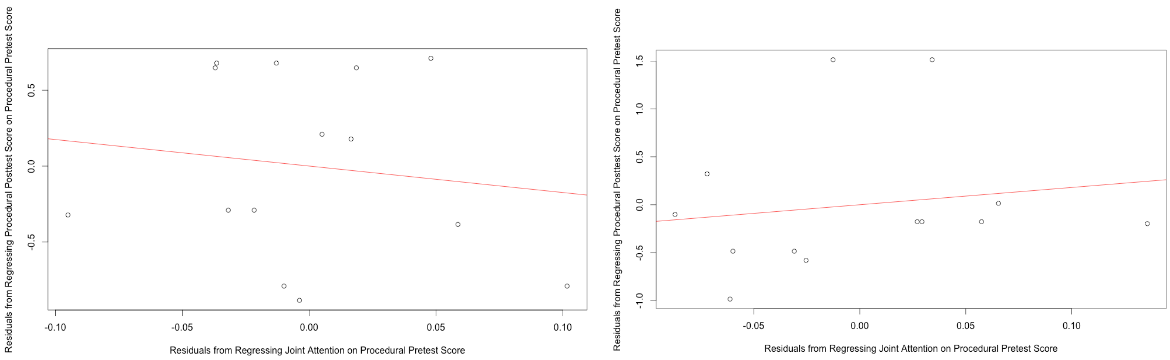

Figure 6. Partial correlation of joint visual attention with posttest scores on procedural knowledge for students in the conceptual condition (left) and in the procedural condition (right)

Discussion

Our project studies learning in a collaborative tutoring environment. One of its aims is to utilize multiple data sources, including dual eye tracking, to understand relations between joint visual attention, dialogue, problem-solving performance, and learning. In this chapter, we explore different roles that dual eye tracking, in combination with other data sources, may play in understanding these relations. It may help advance our understanding of how dual eye tracking can be useful in understanding collaborative learning.

Although the correspondence of eye gaze with speech has been studied before, it is still an open question of whether and 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. Nor, to the best of our knowledge, has dual eye tracking been used before to study mathematics learning of elementary school students, supported by ITS software. 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. These areas provide a broad structure and illustrate the potential of dual eye tracking especially when used in conjunction with other data streams. They present some interesting, if sometimes unexpected, findings that warrant further investigation.

To what degree does dual eye tracking contribute to understanding collaborative learning processes? Through our analysis, we found that subgoals where talk occurs have a higher level of joint visual attention than subgoals without talk, extending previous work (Richardson, Dale, & Kirkham, 2007) to younger learners and to working in an ITS environment. This result suggests, in line with prior work, that speech can help coordinate joint visual attention, for example by referencing items on the screen. Interestingly, it can do so even in a task environment that may already drive eye gaze to certain areas of the screen – in the tutor, there is step-by-step guidance and subgoals are revealed one at a time, which may provide a strong suggestion to the collaborating partners of where to place their attention. Contrary to our hypothesis, we did not find greater joint visual attention on subgoals where students made errors. Apparently, if errors are occasion for more frequent or more intense collaboration, as our analysis of the speech data suggests (Olsen, Rummel, & Aleven, 2015), this effect does not manifest itself through increased joint visual attention. It may be that neither tutor feedback marking the error in red on the screen, nor discussion of errors with a partner, causes greater joint visual attention than answering the item originally. It is possible that errors may not lead to greater collaboration, although that would be inconsistent with the speech data. Alternatively joint visual attention, especially when considered at the subgoal level, may be too temporally coarse-grained as a measure of collaboration. Analyzing the joint visual attention immediately after an error (i.e., at a finer temporal grain size) may provide a better indication of the effect of errors on joint visual attention.

In addition, we found differences in the level of joint visual attention associated with three tutor features designed to support collaboration, albeit in somewhat unexpected ways. Contrary to our expectation, subgoals supported through cognitive group awareness had a lower level of joint visual attention compared to those supported through roles. We must note that this conclusion is tentative, as the analysis does not fully separate the effect of the specific type of fraction subgoal (e.g., whether students are trying to understand factors versus the notion that the numerator and denominator are multiplied by the same number for equivalent fractions) from that of the specific type of collaboration support. Not all problem types were crossed with all support types. Nonetheless, it is interesting to ask why subgoals with the cognitive awareness feature may have lower joint visual attention than those with roles. Recall that on subgoals supported through cognitive group awareness, students first answer a multiple choice question individually (see Figure 1), they then get to see their partner's answer, and then (presumably after discussing their individual answers, at least if they differ) provide a consensus answer. Although students may have their attention on this same question, they may not be looking in the same area of the question because they are trying to understand the visual information that came from their partner. It may be, as well, that the students do not discuss the group answer before entering it, so that a common verbal reference that would guide the eye gaze is lacking. More temporally fine-grained analysis of joint eye gaze may help shed light on this somewhat speculative interpretation. Alternatively, it may be worthwhile to consider whether there is greater joint visual attention (perhaps coupled with more talk) when the partners' individual answers diverge. On the other hand, when the students were supported through roles, they may be able to follow along as their partner submits an answer to a step, which would lead to a higher level of joint visual attention. When there is little talk, visual attention is the key way that the partner would know when the solution to the step has been entered to the problem by watching their screen. Here again, more fine-grained analyses of eye-tracking data may help.

Finally, it is important to look at correlations between joint eye gaze and learning outcomes, as these correlations would provide support for joint visual attention as an indicator of the degree to which the students might be collaborating productively (Jermann et al., 2011; Richardson & Dale, 2005). As hypothesized, we found joint visual attention to be a significant predictor of conceptual posttest scores. Contrary to our hypothesis, this correlation was found only in the procedural condition, in which students solve problems aimed at supporting procedural learning. Also, contrary to our hypothesis, we found no correlation between procedural learning and joint eye gaze. Combined with our finding that of learning gains for conceptual knowledge, we might infer that collaboration and joint visual attention may be important for conceptual knowledge specifically when it is not being directly supported. When conceptual knowledge is already supported in the tutor, there may be no additional gain for students to be working together and may have less joint eye gaze. The difference in correlation might also be due to the way the problems are developed. The conceptual problems tend to be much more text heavy than the procedural problems, which may lead themselves to having less overall joint eye gaze.

Our results show the potential of using dual eye tracking to better understand collaboration, especially when used in conjunction with other data streams although there are some limitations with our small sample size and it is unclear how our results would generalize outside of our dataset. However, our analyses do suggest that dual eye tracking can reveal additional information not evident in other data streams, and that analysis with other data streams can help guide the process of considering tentative interpretations based on eye tracking data. We see this in all three of our different analyses. For our analysis of the correlation between talk on a subgoal and joint eye gaze, we showed there was a relationship within our dataset, which provides information beyond just the student speech that students might be connecting problem features that they see through their dialogue. For the collaborative features used in the tutors, we gained further insights on which features may have an impact on collaboration by analyzing how joint eye gaze differed between the different features. In terms of learning, we also found a correlation of conceptual learning with joint eye gaze for students working procedurally. This may provide some insights about when collaboration may be appropriate for students during the learning process. Together, all of these analyses show the benefit of analyzing educational data in conjunction with joint eye gaze.

For future work, we would like to expand the three areas of analysis around dual eye tracking beyond joint visual 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. For example, an AOI analysis might help us distinguish between joint visual attention on areas with text versus graphical representations, and whether patterns of distributing attention between these representations differ between students working individually and collaboratively. In addition, in our analyses so far, we have analyzed joint visual 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 address a wider range of questions. In this chapter, we have shown that dual eye tracking can be combine with other process measures to shed light on the mechanisms of collaborative learning process that may otherwise not be accessible. By understanding how these different data streams relate to one another, future work can use a mix of the data streams to better understand the dyad's learning outcomes and how the individual contributes to that learning. In this chapter, we looked at joint eye gaze with overall learning gains, but there are other process measures as well that may be used along with joint eye gaze to provide a more complete picture. The group answers of the team are recorded within the tutor logs, providing a measure of the dyad's process within the tutor. By combining the tutor logs with other process data, such as speech and eye gaze, we may be able to measure the individual contributions to the group by understanding which student may have suggested an answer and if a certain student is leading the discussion through leading the eye gaze. By combing the different data streams, we may be able to better understand the interplay between students that leads to a successful collaboration and beneficial learning.

Acknowledgments We thank the CTAT team, Michael Ringenberg, 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).

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