Computer-Supported Collaborative Learning (2013) 8:455–485
DOI 10.1007/s11412-013-9184-1

Capturing and analyzing verbal and physical collaborative learning interactions at an enriched interactive tabletop

Roberto Martinez-Maldonado · Yannis Dimitriadis · Alejandra Martinez-Monés · Judy Kay · Kalina Yacef

Received: 1 March 2013 / Accepted: 3 October 2013 / Published online: 13 November 2013

Abstract Interactive tabletops can be used to provide new ways to support face-to-face collaborative learning. A little explored and somewhat hidden potential of these devices is that they can be used to enhance teachers' awareness of students' progress by exploiting captured traces of interaction. These data can make key aspects of collaboration visible and can highlight possible problems. In this paper, we explored the potential of an enriched tabletop to automatically and unobtrusively capture data from collaborative interactions. By analyzing that data, there was the potential to discover trends in students' activity. These can help researchers, and eventually teachers, to become aware of the strategies followed by groups. We explored whether it was possible to differentiate groups, in terms of the *extent* of collaboration, by identifying the interwoven *patterns of* students' *speech* and their *physical actions* on the interactive surface. The analysis was validated on a sample of 60 students, working in triads in a concept mapping learning activity. The contribution of this paper is an approach for analyzing students' interactions around an enriched interactive tabletop that is validated through an empirical study that shows its operationalization to extract frequent patterns of collaborative activity.

Keywords Collocated computer-supported collaboration · Group awareness · Interactive tabletops · Sequence pattern mining

Introduction

Research on learning and instruction has shown that *collaboration* can lead to improved critical thinking, reduced task workload, increased retention, and a more positive attitudes towards the subject matter (Felder and Brent 1994; Johnson and Johnson 1986). Particular cognitive mechanisms that may result into learning have an increased probability to be triggered when students argue to convince others to change their views on problems, reach shared understanding, or integrate individual with group knowledge (Scardamalia and

R. Martinez-Maldonado (✉) · Y. Dimitriadis · A. Martinez-Monés · J. Kay · K. Yacef
The University of Sydney, Sydney, NSW, Australia
e-mail: roberto@it.usyd.edu.au

Bereiter 1991; Stahl 2006). This makes collaboration skills key conditions for value generation, not only for learning but also in the workplace (Scheuer et al. 2010).

However, students working together to achieve a shared goal do not spontaneously collaborate (Dillenbourg 1998), even if they are supported by a computer system (Kreijns et al. 2003). Collaborative learning is not a single mechanism; it often requires all group members to engage on a coordinated effort to provide a joint solution to a problem (Roschelle and Teasley 1995). It also demands the development of a number of skills, and thus teachers have a central role in providing feedback and helping students to be more aware of their group dynamics (Dillenbourg et al. 2011; Kirschner 2001; Slavin 1983; Webb 2009).

Face-to-face collaboration offers *particular* benefits that are not easy to achieve in other forms of group work (Johnson et al. 2000). These include a natural channel for continuous interaction, exchange of non verbal cues, and increased productivity in completing tasks (Olson et al. 2002). The classroom is an environment where teachers commonly conduct small group activities to promote students' learning and collaboration (Leonard et al. 1997). However, teachers have to manage their limited resources, particularly in terms of the attention they can give to each student, each with different learning styles, strengths and needs (Zhang et al. 2004). They may try to identify the groups that are collaborating more effectively and leave them to work more independently so that they can focus on groups that need more attention. As a teacher cannot attend to all groups at once, they generally cannot be aware of the process that some groups followed (Race 2001).

The development of emerging pervasive shared devices, such as *interactive tabletops*, is very promising for providing a new form of support for students to collaborate and for teachers to monitor group work (Kharrufa 2010). The affordances of interactive tabletops include the provision of a work space that offers equal opportunities for each learner, repeatability when working with virtual content, and digital tools that give students access to different resources for building a solution (Piper and Hollan 2009). Tabletops provide an environment in which students can decide whether they work in parallel, or together as a group (Martinez-Maldonado et al. 2012b). They also open up new opportunities for capturing learners' *digital footprints,* creating the possibility that teachers and researchers can gain new understanding of the collaborative processes. In particular, there is the promise that analysis of the digital footprints can be used to recognize patterns that can distinguish *higher* from *lower achieving* groups (Martinez-Maldonado et al. 2011c).

There is a large body of research on the analysis of computer-supported collaboration (Soller et al. 2005), and on the emerging fields of Educational Data Mining (Baker and Yacef 2009) and Learning Analytics (Siemens and Baker 2012). However, most of the proposals for automatic analysis have considered networked settings, where, in principle, all the interactions between students can be recorded by the system (Soller et al. 2005). When applied to face-to-face settings, computer supported collaboration analysis is mostly based on video and audio recordings (Jeong and Hmelo-Silver 2010), and oriented to researchers, whose focus is on the deep and detailed insights enabled by streams of data.

Teachers need tools that can provide them with coarse-grained feedback that allows them to monitor what is happening in their classes (Dillenbourg et al. 2011). One challenge in the field is to create reliable indicators of collaborative work that can be used by teachers to monitor the activity, and by students to self-regulate their collaboration. Additionally, co-located collaboration is strongly based on verbal, as well as subtle non-verbal, interaction and therefore important aspects of the communication are not mediated by the technology. The integration of evidence of verbal activity with the data stored by the learning systems is not straightforward. For this reason, most of the tools that provide support to teachers, even if applied in face-to-face settings, do not include these verbal utterances as part of the automatic input, yet it is very important. There is a need to provide technological infrastructures that are able to integrate these verbal interactions. This leads to a more important need, which is the definition of analysis methods that exploit this integration.

We present an approach to exploit the affordances of an interactive tabletop to automatically and unobtrusively capture students' *verbal interactions* (speech), their *physical* activity (touches on the tabletop) and their *knowledge representations* to produce indicators of collaborative work. These indicators can make visible the strategies followed by students and highlight possible problems in small group work. The contribution of this paper is an approach for capturing and analyzing students' interactions around an enriched interactive tabletop, which is validated with an empirical study showcasing its operationalization for extracting frequent patterns of collaborative activity.

The specific face-to-face collaborative context of our work is *a small group learning activity in an enriched interactive tabletop*. We identified the *sources* from which information can be captured in this kind of learning environment: the group as a hole, individual contributions, and the digital artifacts they create during the learning activity. We also identified the *target users* of the data analysis. These typically are: (i) the learners, (ii) their teacher, (iii) researchers, or (iv) the learning environment itself. There are three main components of our approach: data capture, data analytics, and data presentation. The *Data Capture* component gathers rich contextual information from the tabletop environment (in this study: identified actions, detected speech and aspects of the collaborative concept maps). The *Data Analytics* component can transform the captured data to produce key indicators of interaction or possible strategies followed by students. The third component, *Data Presentation*, which is beyond the scope of this paper, has the potential to provide the target users with results of the data analysis in the form of a teacher's dashboard or knowledge. This paper is limited to present key information to be directly used by researchers or that can be used to implement a recommended system for further stages. The design of such a system is important and independent from the focus of this paper, although some promising work towards it has been reported (Martinez-Maldonado et al. 2013) and this points to the potential of our approach for broader uses.

The paper is organized as follows. The next three sections present the state of research on interactive tabletops in education, collaboration analysis and concept mapping. Then, we describe our technological infrastructure. After this, we present our research questions, the design of the study, and an exploratory analysis of the captured data. Then, we describe our approach to extract patterns of activity by applying a sequence mining technique. We discuss the results in the final section.

Collaborative learning around interactive tabletops

The proliferation of surface devices, such as tablets, smart phones, and more expensive tabletops, is causing a shift in the possible ways that people can interact with computers (Hilliges et al. 2010). This is creating opportunities to make computers more ubiquitous rather than the center of the activity as is often the case with most of desktop/laptop computers. In particular, interactive tabletops can enrich a typical face-to-face setting by providing unconstrained orientation of a shared space, allowing the placement of physical items, and offering each group member equal opportunity to participate (Müller-Tomfelde and Fjeld 2012). However, like other technologies, tabletops themselves do not provide a direct improvement in learning or collaboration. Instead, they open the possibility of new ways to design activities that teachers and researchers can take advantage of, to enhance instruction (Dillenbourg and Jermann 2010).

The common denominator of most of the research on tabletops for education is the study of some interaction data, mainly obtained from observations and activity logs that the hardware can capture, to support qualitative analysis of collaboration. A few examples include the use of group observations to reveal social relationships (Falcao and Price 2009; Fleck et al. 2009; Rogers and Lindley 2004), the analysis of symmetry of interaction based on the number of learner's touches (Harris et al. 2009; Rick et al. 2009), quantitative measures of verbal turn taking and communication (Jermann et al. 2009; Marshall et al. 2008; Martinez-Maldonado et al. 2012c; Rick et al. 2011), the exploration of the impact of users' positions around the tabletop (Tang et al. 2010), the assessment of group products (Do-Lenh et al. 2009; Kharrufa 2010; Oppl and Stary 2011) and the analysis of the process of scripted collaboration (Kharrufa 2010).

One of the most promising examples of work where the use of tabletops can directly help teachers is deploying multiple tabletops in the classroom. One approach was presented by AlAgha et al. (2010), who designed a multi-tabletop classroom, orchestrated by a teacher's monitoring tool. This setting offers students the opportunity to work face-to-face, and they have access to multimedia content. It also allows the teacher to monitor, orchestrate and improve the class management by controlling students' tabletops remotely (Mercier et al. 2012). A second approach by Martinez-Maldonado et al. (2012a) explored the use of multiple tabletops in an authentic classroom. Notably, that work provided explicit support for the teacher to design, enact and assess small group activities linked to the curriculum.

However, most of these studies were done not for the purpose of exploiting data automatically. Some exceptions include the visualization of tabletop data to increase teacher's awareness (Al-Qaraghuli et al. 2011; Martinez-Maldonado et al. 2012b), the use of data mining to discover differences between groups (Martinez-Maldonado et al. 2011c) and an approach to analyze logs to assess teachers' activity design (Martinez-Maldonado et al. 2012a).

The analysis of verbal participation in non-interactive tabletops has shown that even modest indicators of speech, that can be automatically captured, are effective in supporting inferences about important aspects of collaboration. These include: interaction patterns, the evolution of the discourse flow, leadership, and behavioral changes (Roman et al. 2012). The automated analysis of verbal participation in interactive tabletops is an important aspect where there has been little research (Martinez-Maldonado et al. 2012b). Previous research has also investigated the impact of multi-user interactions afforded by tabletops on certain aspects of collaboration such as equity of participation and self-regulation (Marshall et al. 2008). A deep understanding of the connection between the speech and physical dimensions of the interactions in the tabletop is still lacking. The next section describes how research on online collaborative systems can serve as a basis for analyzing collaboration in the tabletop.

Collaborative learning analysis and mining

Over the last two decades, there has been substantial progress in the development of technologies that enable learners to collaborate, mainly through networked systems (Soller et al. 2005). Large amounts of data can be captured as a result of the interaction of students with these systems and, indirectly, with their peers. Students' activity can be recorded at different levels, from video capture, that has mostly been manually analyzed, to logging the system events that can be automatically analyzed by software tools. Students' data can be used for self-regulation (by students); for scaffolding, coaching and evaluation (by teachers); or for post-hoc analysis, design-based interventions, etc. (by researchers). This information can be presented to the actors through visualizations so that they can quickly interpret the information and take appropriate actions. Software agents can also trigger automatic regulating actions.

The use of Data Mining or Artificial Intelligence techniques in collaborative learning environments has proven successful in gaining insights on the interactions within groups in terms of collaboration. Some research has studied collaborative learning by applying data mining techniques. Notable is the work done by Soller et al. (2002), who used Hidden-Markov Model to identify the episodes when students were sharing knowledge at a constrained and scaffolded object modeling networked system. Other key initial work was conducted by Talavera and Gaudioso (2004) who presented a case in which they applied a clustering technique to e-learning data; they were able to build student profiles based on a set of features related to the user interaction with the system. Building on this previous work, Anaya and Boticario proposed both a supervised classification (2011) and unsupervised clustering (2009) techniques for grouping students according to their level of collaboration. Additionally, some researchers have addressed the analysis of collaboration using sequential pattern extraction. One important study on online learning data was performed by Perera et al. (2009) who explored the use of sequence mining alphabets and clustering to find trends of interaction associated with effective group work based on data from long term use of a collaborative software development tool.

Most of these examples are based on learning settings where most of the recorded communication is mediated by the system, making it easier to automatically log students actions compared with face-to-face environments. Alternatively, in these examples it is commonly ignored that students can interact face-to-face or via other media (e.g., emails, chats or IM). There is less research in developing systems that can support collocated collaboration and automatically analyze students' data compared with networked systems (Jeong and Hmelo-Silver 2010). Yet, research on *collaboration* through these systems, can provide the foundation for automated capture and analysis of face-to-face interaction through tabletops.

Work on the *analysis of indicators of collaborative learning* can be found as subsets of research in learning analytics (Siemens and Baker 2012), educational data mining (Baker and Yacef 2009) or analysis of collaborative interactions (Harrer et al. 2009). These fields have created techniques to produce models and indicators of learners in a wide range of technology-based learning situations. The analysis can be targeted to develop meta-cognitive support, enhance regulation, facilitate assessment, or improve awareness. Dimitracopoulou et al. (2006) presented a taxonomy of indicators that can be used to represent aspects of *group interaction*, for example, *collaboration intensity, participation rate,* or *division of labour*. Some of these indicators, such as *quality of collaboration* or *common understanding* are difficult to detect even through human judgment. Therefore, they impose limitations to what can be measured automatically.

The *Data Capture* and *Analytics* components of our approach are highly influenced by the taxonomy of group indicators proposed by Dimitracopoulou et al. (2004). This defines the indicators of collaborative work that can automatically be captured and processed from non face-to-face learning systems. This taxonomy sets an initial standard, which can be extended to face-to-face settings. It informs the definition of what data should be captured by a collaborative learning environment that is intended to produce indicators of group activity. It distinguishes five sources of information for analyzing the collaborative process: (i) individuals (the actions and products of specific learners), (ii) undifferentiated group (information that concerns the whole group, without identifying individual contributions or roles), (iii) differentiated group (information in which the contribution of each learner is identified), (iv) the community (considering multiple groups), and (v) the society or community). Our approach concerns only the first four aspects.

In face-to-face settings there is substantially more information being externalized by learners in comparison with networked applications, for example, hand gestures, body language and gestures of assent, among others (Olson et al. 2002). The collaborative situation and channels of communication are significantly different in collocated settings. Therefore, the technology can capture some aspects of students' interactions in a face-to-face setting (Yu and Nakamura 2010).

Collaborative concept mapping

We combined face-to-face collaborative learning mediated through an interactive tabletop with an educational tool that has the potential to foster students' meaningful learning: *concept mapping*. This is a well established learning strategy that can be applied in a number of domains and is backed up by a strong community of research and practice (Cañas and Novak 2008). Concept mapping enables students to externalize their understanding through a visual representation of knowledge (Novak 1995). A concept map consists of a directed graph in which nodes represent *concepts*. These are defined as perceived regularities in events or objects of a domain (Novak and Cañas 2008). For example: *balanced diet*, *proteins* or *meat.* Concepts can be connected with a labeled link to create a meaningful statement called a *proposition.* For example*,* the concepts *meat* and *proteins* might be linked in the proposition: *meat contains proteins* using the link *contains*. Similarly, the earlier concepts can form the proposition: *balanced diet includes proteins*. Concept maps can serve as vehicles of discussion and negotiation of meaning between students (Novak 1995). They can be used for facilitating collaborative learning, offering students the opportunity to discuss ideas, present knowledge from multiple angles, identify misunderstandings, reach agreement, or agree to disagree (Gao et al. 2007; Novak 1995; Stahl 2006).

Some studies have specifically explored concept mapping at the tabletop. An early example was a single user system that used concept maps for wiki navigation (Baraldi et al. 2006). Tanenbaum and Antle (2009) built a system that permitted a student to create a concept map using tangible tokens. Do-Lenh et al. (2009) compared the use of a tabletop with a shared desktop computer to build collaborative concept maps. Results were negative for the tabletop; because sharing a personal computer *forced* negotiation. By contrast, a tabletop does not force collaboration. Later, Oppl and Stary (2011) found that tabletop concept mapping offers students equal opportunities for participation when compared with other media. Martinez-Maldonado et al. (2012c) also demonstrated that tabletop concept mapping can provide students the opportunity to decide how to coordinate their strategies. Overall, this body of work points to a complex picture of the potential benefits of collaborative concept mapping at tabletops.

System setup

In this study, the data capture, if not comprehensive, is low cost, unobtrusive and very large volume; and it has the promise of generating imperfect, but useful indicators of collaboration similar to those described by Dimitracopoulou et al. (2004) and, more specifically, to address a set of research questions that are described in the next section. We used a number of tools to permit students to create concept maps (individually and collectively) and, we simultaneously capture information of the process followed. These tools are a desktop-based (CmapTools) and a tabletop-based (Cmate) concept mapping tools; and a system to unobtrusively capture differentiated users' actions (Collaid).

CmapTools (Novak and Cañas 2008) is a concept mapping editor for personal computers. In this study, students use it to build their concept maps individually. CmapTools offers an *Extensible Language* based on XML to share and export the concept maps to other environments. We exploit this functionality to connect the artifacts that students first build in private with the tabletop environment that they use to build a new artifact, the concept map created collaboratively in the tabletop.

Cmate (Martinez-Maldonado et al. 2010) is a tabletop application that enables learners to draw a concept map that represents their collective understanding about a topic (Fig. 1, bottom left). Cmate provides each student with a personal menu to add the concepts they used in the concept map that they individually created using CmapTools. Students can also add any new concepts they wish. When students create propositions, a menu appears around the new link so they can select any of the top six linking words they used before or they can type a new linking word. Students also have access to a screenshot of the map that they created in private; this enables them to recall or to share their perspectives with others. Students can decide to build upon their previous concept maps or create a totally new group artifact.

Collaid (Martinez-Maldonado et al. 2011a). The tabletop used in this study had a 46-in. LCD touch screen, offering comfortable space for up to four participants. The tabletop hardware can detect multiple touches at a time, but—like most current touch hardware—it cannot recognize which user provides an input. In order to log each student's individual actions, we used Collaid.

Collaid extends an ordinary interactive tabletop, so that it can unobtrusively determine *which learner is touching what*. It relies on an overhead depth sensor (http://www.xbox.com/kinect) that associates each touch performed on the interactive surface with the student who did the action. The system captures the overhead depth video stream and then, making use of

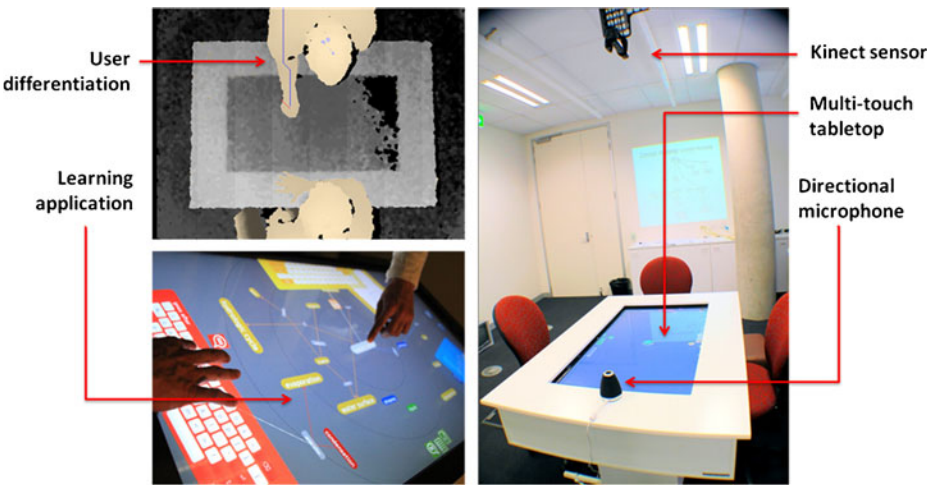

Fig. 1 Digital learning environment and capturing system

a greedy search algorithm, matches the touch with the position of each learner (Fig. 1, top left). We capture verbal participations and turn taking through a microphone array situated on one of the edges of the tabletop (Fig. 1, right). We used a 7-channel microphone (http://www.dev-audio.com) that distinguishes sounds based on the location of the source. In our case, the learners sit around the tabletop. The audio information is recorded into audio files and the shared database.

Through this set of software and hardware, we can capture a multi-dimensional dataset: verbal interactions between learners, without attaching microphones to people; and tabletop data logs with the authorship of each touch at the tabletop, without attaching any gadget to learners' hands or imposing additional hardware restrictions. Figure 1 shows the generic hardware we used, including the sensors.

Study design and exploratory analysis

This section describes how we designed a study to assess whether the data captured in a tabletop learning environment can provide useful information about learner collaboration. We began by formulating research questions; these come from considering open issues in previous studies on collaboration in tabletops and the potential power of our four data sources (audio, touch, touch on other learner's artifacts and access to individual perspectives). Next, we describe the design of the study to identify interaction patterns around tabletops.

Research questions

We identified four research questions that link the observable patterns or strategies that are promising for differentiating groups according to the *extent* of their collaboration. First, previous research on collaboration around interactive and non interactive tabletops suggested that groups that produce *better* solutions have more equality in discussion (Martinez-Maldonado et al. 2012c; Roman et al. 2012). This finding motivated our first two questions; these primarily focus on the exploration of *verbal activity*, and its timing in relation to the *physical* tabletop *activity*.

1) Can we distinguish more collaborative from less collaborative groups by the interwoven stream of students' *verbal and physical participation*?
2) Can we distinguish more collaborative from less collaborative groups by extracting patterns of interaction based on just students' *verbal participation?*

Other studies inspired our third question; these suggested that when a learner interacts with digital artifacts created by other students, this may trigger further discussion that is beneficial for collaboration (Fleck et al. 2009; Martinez-Maldonado et al. 2012b). In the context of collaborative concept mapping, this may be associated with the concept of *transactivity,* which is the extent to which one group member refers to, or builds their own ideas upon, their peer's contribution (Molinari et al. 2008; Stahl 2013). Strictly, this would be measured in terms of the number of links that each learner creates using concepts that other learners added to the group map (Martinez-Maldonado et al. 2012c). Our approach goes a step further by including all the interactions a student performs on others' objects, including moving them. The third question is:

3) Can we distinguish more collaborative from less collaborative groups based on patterns involving *traces of interaction of students with others' objects*?

We also explored the strategies followed by different groups to access individual learners' representations of knowledge inspired by the studies on mutual awareness by having access to individual concept maps (Engelmann and Hesse 2010). The fourth question is:

4) Can we distinguish more collaborative from less collaborative groups in terms of the actions that follow up the access to others' knowledge structures?

Participants and approach

One approach that has proved successful to foster meaningful learning is to follow the construction of individual concept maps with a collaborative phase (Engelmann and Hesse 2010; Novak 1995). This provides students with the opportunity to first think about their personal understanding and then focus on establishing common ground with others, negotiating meanings, and generating group knowledge. This strategy is supported by the theory of *Group Cognition* in which the process of knowledge building is modeled as a continuous loop of individual and collaborative periods of learning (Stahl 2006). Our approach builds on these approaches by providing both an individual and a shared space for group members to build concept maps.

A total of 60 students enrolled in science courses participated in the study. An initial focus question was posed to the students: What types of food should we eat to have a balanced diet? Their goal was to create concept maps after studying the Australian Dietary Guidelines 2011 published by the National Health and Medical Research Council of Australia. Participants were organized in triads mainly grouped so they knew each other. Before the activity, students received instruction on concept mapping and were requested to draw a training concept map not related to the nutrition domain. Then, they were asked to read a one-page article based on the dietary guidelines and draw a concept map individually at a personal computer using CmapTools (Fig. 2, 1). After this, each triad was asked to build a concept map in the tabletop (Fig. 2, 2). This application was loaded with the individual maps previously built, allowing learners to have access to the concepts, linking words and an image of their maps. The group activity was structured in two phases: i) *brainstorming,* where students were only asked to add the most general concepts for their joint map without creating propositions (they were advised to dedicate the first 5 to 10 min for this); and ii) *linking*, where students could create propositions and add more concepts if needed (20–25 min.). They had 30 min for building individual maps and 30 min or more for the collaborative step. Finally, each learner was asked to draw an individual map again (Figs. 2 and 3).

In this study we made a clear distinction between the brainstorming and linking phases since the learning goals, the duration and the range of students' actions are different for both activities. Therefore, we describe the exploration and analysis of students' data for each of them separately. Our research questions are aligned with this exploratory approach. Through these, we show that the same approach is applicable, and the results can be informative, for both classes of learning activity.

Meaningful physical actions

The tabletop application initially provides each learner with three tools: a list of concepts, an onscreen keyboard for editing phrases, and a resizable representation of their individual concept map. Learners can add concepts by simply selecting them from

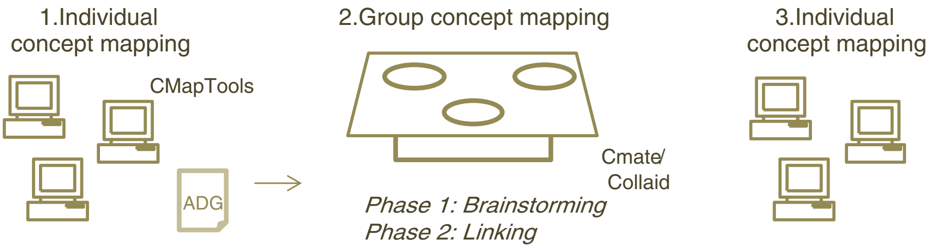

Fig. 2 Learning setting: *1*) concept mapping based on the Australian Dietary Guidelines (ADG); *2*) group concept mapping; and *3*) individual concept mapping

a list that contains those they each used when building their individual map externally. They can add links by dragging a concept and dropping it on another concept; and delete elements by dropping them on one of the two black holes at the corners of the tabletop.

All elements of the tabletop are colored according to the user who created the object. In this paper, we distinguished between the touch events captured by the tabletop hardware and what we call *meaningful physical actions,* which produce a change in the collaborative artifact. For example, to add a concept, a learner can search for the desired word from their list or decide to create a new concept. For simplification we associated all the touch events with only one higher-level action: *adding a concept*. The *meaningful physical actions* are illustrated in Fig. 3. These include adding, deleting, editing and moving concepts or linking words, and accessing individual maps on the tabletop. For the brainstorming phase the interface only allowed students to add concepts from their lists, create new concepts and open their individual concept maps. This includes the core task for this stage, creating propositions.

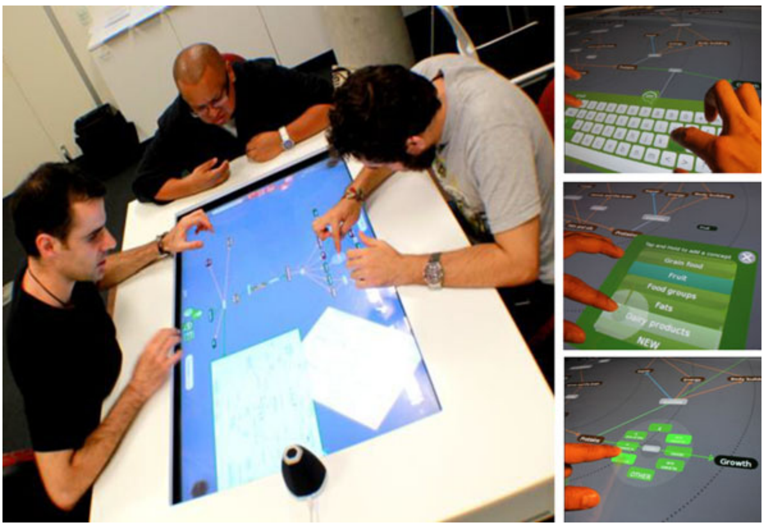

Fig. 3 Meaningful physical actions. Two individual maps are open on the tabletop (*left*). Editing a linking word, adding a concept from a personal list and creating a link from the eight most used in learner's map (*right, top to bottom*)

Quantitative assessment of quality of collaboration

All 20 sessions in the tabletop were assessed quantitatively. The goal of this analysis was to *differentiate* the groups in terms of whether the quality of their collaboration was assessed as high or low. We applied the analysis method designed by Meier et al. (2007) which defines nine qualitative dimensions of collaboration that are rated quantitatively. These dimensions are: mutual understanding, dialogue management, information pooling, consensus reaching, task division, time management, technical coordination, reciprocal interaction, and individual task orientation. The first 8 dimensions are group assessments and the last one includes individual assessments per student. Each dimension is quantified with a whole number ranging from −2 (very bad) to 2 (very good). We aggregated the numerical results of all dimensions to obtain a single score to categories the groups.

An aggregated score below zero was treated as *less collaborative* (or low collaboration) and positive scores as *more collaborative* (or high collaboration). This gave 10 groups with negative scores (−10 to 0). The other 10 groups had scores from 5 to 19. The averages were −4 (±3) (low collaboration) and 13 (±5), (more collaborative), where these differ by at least twice the standard deviation in each case. Two different raters tagged the sessions following the same rubrics as (Meier et al. 2007). Inter-rater reliability was high (Cohen's k = 0.80). This qualitative rating scheme was useful to generate a quantitative measure to distinguish the groups. However, it still has the limitation of requiring human judgment. There is ongoing research that aims to automate part of this assessment to offer a rating using a machine learning model, so making it possible to provide direct insights to teachers or perform analysis on the fly (Martinez-Maldonado et al. 2013).

Preliminary analysis

Before any pattern mining was undertaken, we explored the data to analyze if, by using simple statistics, it is possible to distinguish groups in terms of their extent of collaboration. First, we looked at the time that each group spent in each phase.

Table 1 shows the time spent by both more collaborative and less collaborative groups to complete the activity. We can observe that the majority of more collaborative groups kept to the suggested time for each phase (5–10 and 20–25 min respectively). While the less collaborative groups had similar averages, they had higher deviations. Even though the differences are not statistically significant, this suggests that some groups spent either less or more time of the allocated time for both phases. The issue to address is whether quantitative data can provide insights of the strategies that lead these groups to be less collaborative.

To further explore the dataset, we draw on previous work by Martinez-Maldonado et al. (2011b, 2012b), who modeled quantitative information of students working at a shared device, for three aspects of tabletop collaboration: *physical interaction*, *verbal interactions,* and the synergy between these two. We analyzed the *brainstorming* and *linking* phases separately as the range of actions and learning objectives were different. First, regarding the *physical activity*, we explored the cumulative interaction by each learner with other students' objects through the visualizations designed by Martinez-Maldonado et al. (2012b).

Table 1 Average time taken by groups to complete each collaborative phase

	More collaborative	Less collaborative
Phase 1 (brainstorming)	10′ (±3)	10′ (±7)
Phase 2 (linking)	21′ (±2)	24′ (±9)

*Time in minutes

Figure 4 shows three examples of the visualizations, where the size of the circles indicates the number of touches by learner. The thickness of the lines linking the circles represents the amount of interaction between pairs of learners, in terms of actions on objects created by the other. The visualization in Figure 4-*a* corresponds to a group that behaved quite collaboratively on this aspect. It shows three similar sized size circles, each linked to the other, with two lines, albeit each of various widths. Groups that are less collaborative groups on this dimension are illustrated in *b* and *c*, with different sized circles and, notably in *c* just one connection of the green using acting on objects of the yellow user.

Additionally, it has been found that for tasks like ours that called for equal participation, groups in which learners participate asymmetrically sometimes indicate cases of social loafing or disengagement (Dillenbourg 1998). For this, we explored one indicator of symmetry that has been used to study collaboration in tabletops: the G*ini coefficient* (Harris et al. 2009). This is a measure that represents *inequality* with a single number between 0 and 1, where 0 is perfect symmetry and 1 total inequality. Previous work with tabletops has found that coefficients close to 0.5 can be associated with non equal activity (Martinez-Maldonado et al. 2012c). Table 2 summarizes the amount of physical activity in our triads, the interaction of learners' with others' objects and the symmetry.

According to Table 2, for the *brainstorming* phase, all groups (both more and less collaborative) had similar levels of physical activity and high symmetry (>300 raw touches, gini coeff. 0.18). The main difference between Phase 1 and 2 was that in the *linking* phase, learners interacted more (and more unequally) with objects created by their peers. Overall, the level of action on others' objects was 29 % for high groups and 25 % for low groups.

For the symmetry of physical activity, the high groups, shifted to less symmetric (rising gini coeff. from 0.18 to 0.35) while the low groups were rather consistent, 0.18 to 0.20). In fact, learners in low groups appeared to show more equality in their physical activity, consistent with the trend reported in (Martinez-Maldonado et al. 2011b). Contrary to what the visualizations of Figure 4 suggest, we found that low groups had more signs of symmetry in the physical interaction with other's objects (gini coeff. 0.2 for low and 0.36 for high groups). However, there were no significant differences that could distinguish groups as either more or less collaborative. Overall, these simple analyses provide a rather complex picture that makes it unclear how a group of learners, or their facilitator or teacher, might make use of these measures.

Secondly, we explored simple indicators of speech that might provide hints of possible issues in group work. Table 3 shows that the more collaborative groups had higher levels of verbal activity. In Column 1, we see time spent speaking of 457 against 270 in Phase 1 and 773 against 531 for Phase 2. For the number of utterances, in Column 3, there is a similar situation, with 138 against 91 in the brainstorming phase, 229 against 109 in the *linking*

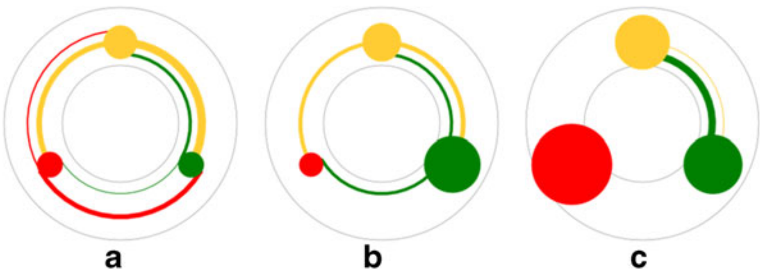

Fig. 4 Graphs of interactions with others' objects for (**a**) a collaborative group, **b** a group with a passive student, and (**c**) a non-collaborative group

Table 2 Average values of physical activity, interaction with others' objects, and symmetry

	Collaboration	Physical activity (touches)	Physical activity (symmetry)	Touches on others' objects	Touches on others' objects (symmetry)	Touches on others' objects (% all actions)
Phase 1 (brainstorming)	Low	344 (±184)	0.18 (±0.1)	39 (±54)	0.63 (±0.3)	10 % (±10)
	High	320 (±120)	0.18 (±0.1)	32 (±25)	0.63 (±0.2)	9 % (±7)
Phase 2 (linking)	Low	897 (±475)	0.20 (±0.1)	211 (±80)	0.20 (±0.1)	25 % (±6)
	High	740 (±120)	0.35(±0.1)	205 (±78)	0.36 (±0.2)	29 % (±11)

phase. Both phases had greater symmetry for the high collaboration groups (Column 2, gini coeff. 0.19 against 0.34, then 0.19 and 0.30 for the linking phase). Even though the large standard deviations affect the analysis of significance, these indicators suggest trends that point to the potential value of deeper exploration at a lower level of granularity.

Table 3 also shows the average values of what we call *meaningful physical actions*, which affect the size, shape or content of the group artifact. We observed no difference between low and high collaborators in the number of these actions for the *brainstorming* phase (114 and 105 actions respectively) but some difference in the *linking* phase, where the less collaborative groups had more of these actions. Lastly, we also accounted for the number of times group members accessed their *individual maps*. The main difference was that the more collaborative groups *always* accessed their maps, while *some* of the low groups never opened a concept map (deviations equal to the average).

We additionally explored the *relationship between verbal and physical actions*. Previous work by Martinez-Maldonado et al. (2011b, 2012b) suggested that the more collaborative groups had higher levels of symmetric speech and lower levels of physical actions when using a tabletop. They proposed a way to visualize this with a radar that showed the amount and symmetry of physical and verbal activity. The triangles in Fig. 5 depict the number of touches and amount of speech by each learner (red and blue respectively). Each small circle represents a student. The closer the corner of the triangle is to a circle, the more that a student was participating. An equilateral triangle means that learners participated equally. Figure 5 shows the representations of three groups. Visualization *a* shows a collaborative group in which the 3 learners participated quite equally on both dimensions. Visualization *b* shows a disengaged learner from the activity (left lower red circle); and visualization c shows a learner who had a high level of physical activity but little verbal participation (also left lower red circle).

Table 3 Average values of verbal activity, meaningful physical actions and number of accesses to individual concept maps at the tabletop

	Collaboration	Audio time (seconds)	Audio time (symmetry)	Utterances	Meaningful physical actions	Access to individual map
Phase 1 (brainstorming)	Low	270 (±297)	0.34 (±0.19)	91 (±84)	105 (±65)	4 (±4)
	High	457 (±286)	0.19 (±0.20)	138 (±86)	114 (±53)	7 (±5)
Phase 2 (linking)	Low	531 (±519)	0.30 (±0.13)	109 (±176)	407 (±227)	7 (±7)
	High	773 (±366)	0.19 (±0.07)	229 (±106)	286 (±50)	8 (±3)

Meaningful physical actions = Actions that made an impact on the collaborative artefact only

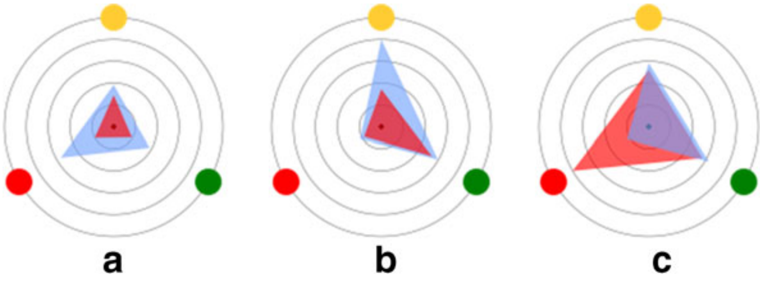

Fig. 5 Mixed radars of verbal (*blue/light triangle*) and physical (*red/dark triangle*) participation for (**a**) a collaborative group, **b** a group with a passive student, and (**c**) a non-collaborative group

Table 4 presents the analysis of the *physical actions* and how these were associated with verbal activity. First, we observed a weak trend in the less collaborative groups performing more physical actions without speech (Column 2, 20 % and 75 % of all actions for low compared with 13 % and 64 % for the high groups). By contrast, for actions accompanied by speech, we found that in all groups, individual learners tended to not to talk while performing physical actions (Columns 3 and 4).

For the *brainstorming* phase just the 16 % of such actions were performed in high groups and 14 % in low groups. For the *linking* phase this proportion was even lower (below 10 %). For the case of physical actions where the speech was from another learner, we found a different situation. An average of 44 % of the actions by the more collaborative groups were performed while other students were speaking (29 % of actions for low groups). For the *linking* phase this difference was smaller though but still with some difference (25 % and 17 % respectively).

Overall, the measures of activity presented above, each aggregated in isolation at the end of the activity, were not indicators of significant difference between groups that were either more or less collaborative. These averaged values do not take account of additional fine grain information that can be exploited, like the order, authorship or the balance between verbal and physical actions. This suggests the need to integrate contextual information and multiple sources of information simultaneously. Next, we present our approach that includes such contextual information with the sequence of learners' actions in order to explore patterns that can help to differentiate groups.

Table 4 Average values of physical actions *with no speech* in parallel; and physical actions *with speech* in parallel from the *same* student and *other* students

Collaboration		Actions with *no speech*	Actions with *no speech* (% all actions)	Actions with speech by *the same author*	Actions with speech by *the same author* (% all actions)	Actions with speech by *other author*	Actions with speech by *the same author* (% all actions)
Phase 1 (brainstorming)	Low	76 (±61)	20 % (±8)	14 % (±13)	14 % (±9)	29 % (±22)	29 % (±16)
	High	52 (±44)	13 % (±12)	16 % (±12)	16 % (±9)	45 % (±35)	44 % (±20)
Phase 2 (linking)	Low	307 (±234)	75 % (±23)	29 % (±28)	8 % (±7)	70 % (±64)	17 % (±20)
	High	185 (±73)	64 % (±61)	29 % (±28)	10 % (±6)	77 % (±39)	25 % (±15)

Physical actions= Actions that made an impact on the collaborative artefact only

Method: Data mining approach

One of the data mining techniques that have been used to identify patterns that differentiate high from low achieving students is sequence pattern mining. We used this technique because it takes account of the order of the events in, rather than simply the accumulated statistical analysis in the previous section. For example, Perera et al. (2009) modeled key aspects of teamwork for groups working with an online project management system; the researchers defined *alphabets* to represent sequential events that had promise for distinguishing strong from weak groups. Martinez-Maldonado et al. (2011c) proposed a semi-supervised approach to extract sequential patterns of students' activity at a pen-based tabletop and cluster similar patterns to link them with group strategies. Kinnebrew et al. (2012) presented a *differential sequence mining* method which automatically compares patterns that characterize high and low-achieving learners including contextual information of students' actions. In this paper, we implemented a mixed technique that combined these three previous approaches as described in the next subsections.

The *raw data* for each group initially consists of two long sequences of actions: evidence of *verbal* speech by each learner and identified *touch* actions. These are transformed into a list of *meaningful actions* and *verbal utterances*, which are defined as: *item action* = {ActionType, Resource, Author, Owner, Time, Duration}, where ActionType can be: *Add* (create a concept or link), *Rem* (delete), *Mov* (move), *Chg* (editing a concept or linking word), *Open* or *Close* (individual maps). Resources can be: *Conc* (concept), *Link* (proposition), *Indmap* (individual map) or *Speech* (utterance). Author is the learner who performed the action, Owner is the learner who created or owned the Resource, Time is the timestamp when the action occurred, and Duration is the time taken to complete the action. Multiple touches to perform a single action and interaction with menus were not included. The original filtered sequence obtained for each group had from 434 to 1467 *physical actions* and from 83 to 627 *utterances.*

Data preparation and formatting

Even though the content of each *item action* in its raw format may appear simple, the level of complexity of these data is actually high. Each student's action is associated with rich contextual information obtained by interlacing the three sources of information: student' physical actions on the tabletop application, the identified speech participation and the status of the artifact.

The enriched tabletop can capture not just the students' actions, but it can also link these to whether students were talking whilst interacting with the interface or just talking without touching the table. Furthermore, in terms of the group artifact, student actions can have an impact on the knowledge represented in the concept map or their actions may just modify surface aspects of it. However, not all of this contextual data is relevant to the research questions. In fact, if all this rich contextual information were taken into account when extracting patterns, the information would be too detailed to find *meaningful trends* in the interaction.

For example, whilst the authorship of learners' actions seems likely to be important, the exact detail of who is doing what is not necessarily relevant: if the intention is to detect how often students take turns versus a single student performing a sequence of actions, we only need to know whether actions were performed by the same student or by different students. Suppose that in one group, there is a sequence of actions (A, A, B) performed by two students in the following order: student1-A, student2-A, student1-B. In a second group, a similar sequence occurs but the authorship is different: student 3-A, student1-A, student3-B. Our encoding system must recognize this pattern to be found, regardless of which pairs of the students among 1, 2 and 3 are involved. Consider a second example, for the verbal participation: In one group, two students may perform the following sequence: student1-A and then student2–B. In parallel, a third student may be speaking: student3-utterance for 5 s. In this case, it is important to encode the sequence of events in a way that captures parallelism (e.g., speech and touch at the same time).

We therefore designed several alphabets, to encode the raw item actions at the level of abstraction needed for each research question, so that relevant patterns could be discovered. Next, we describe the design of a number of alphabets to encode student actions into item actions that capture required contextual information.

Alphabets to encode actions and contextual information

Inspired by previous work on design of alphabets to mine group behaviors (Martinez-Maldonado et al. 2011c; Perera et al. 2009) and the suffix nomenclature proposed in (Kinnebrew et al. 2012), we designed four alphabets. Each is associated with one research question, to enable discovery of the relationship between physical actions, presence of speech, verbal responses, parallelism, ownership, concurrency and access to individual maps.

We encode each action using the alphabets in Table 5. The coding for an action has *one keyword from each level.* The first two levels correspond to *Resource* and *ActionType*. Levels 3 and 4 add contextual information. We perform three steps to apply the four alphabets:

i) All *actions* that can be performed on the *resources* are coded with two *keywords,* from Levels 1 and 2;
ii) All the utterances that did not happen in parallel with any touch actions are coded in the same sequence, with 2 keywords: *Speech* and *Shrt* or *Full* for utterances shorter or longer than *u* seconds respectively (u=2).
iii) The keywords from Levels 3 and 4 are added to each action or utterance. These are different for each alphabet.

Next, we present a detailed description of each alphabet focusing on the specific keywords that are added in the third encoding step.

Alphabet 1 seeks to address the first question by exploring the interweaving of *verbal and physical participation traces.* First, it focuses on adding the contextual information about the s*peech that occurs in parallel with physical actions* (Alphabet 1, Level 3). This includes the keywords: *Sauthor*, which represents that the learner was talking while performing an action; *Sother*, which means that another learner was speaking while the author was performing the action; and *NoSpeech*, which means that when the action was performed no learner spoke.

Alphabet 1 also considers the time, order and author of each action to explore if only one student was building the solution or if their work was more reciprocal (by working either concurrently or completely in parallel). This is represented by the keywords in Level 4, which include: *Tsame*, which means that the previous action was performed by the same author; *Tother*, when the previous action was performed by a different learner (consecutive actions with the keyword *Tother* may indicate *concurrent* work); and *Tparallel*, when the previous action was performed by a different learner less than one second earlier, which is

Table 5 Four alphabets. 1) Physical/verbal participation; 2) verbal participation; 3) physical action on others' objects; and 4) access to individual maps. The keywords that characterize each alphabet are highlighted in bold letters

Alphabet 1: Physical-Verbal participation				Alphabet 1: Verbal participation			
Level 1	Level 2	Level 3	Level 4	Level 1	Level 2	Level 3	
Link	[L,C]Add/Rem/Chg	NoSpeech	**Tsame**	Link	[L,C]Add/Rem/Chg	**NoSpeech**	
Cone	Mov/Mult	Sauthor	**Tother**	Conc	Mov/Mult	**Sauthor**	
Indmap	[I]Open/Close	Sother	**Tparallel**	Indmap	[I]Open/Close	**Sother**	
Speech	Shrt/Full			Speech	Shrt/Full	**Start**	
						Resp	
						Assen	
Alphabet 3: Touches on other objects				Alphabet 4: Access to individual maps			
Level 1	Level 2	Level 3	Level 4	Level 1	Level 2	Level 3	Level 4
Obj	[L,C]Add/Rem/Chg	NoSpeech	**Owner**	Link	[L,C]Add/Rem/Chg	NoSpeech	**[I]Pers/NoPers**
	Mov/Mult	Sauthor	**Difowner**	Conc	Mov/Mult	Sauthor	
	[I]Open/Close	Sother		**Indmap**	**[I]Open/Close**	Sother	
				Speech	Shrt/Full	**Start**	
						Resp	
						Assen	

[I] Only applicable for Individual map objects (Indmap)

[L,C] Only applicable for Concepts and Links (Conc, Link)

about the time for users to perceive immediateness (Nielsen 1993). Multiple and consecutive *Move* actions by the same learner were compressed aggregating the keyword *Mult*.

Figure 6 shows an example of a set of eleven encoded *item actions* of one group. The graph shows three timelines for the physical actions and other three for the utterances performed by each learner. The sequence starts with an *add concept* action performed by U1 accompanied by an utterance of the same learner, encoded as follows: *Conc-Add-Sauthor*. Then, learner U3 adds another concept while the first learner is still talking: *Conc-Add-Tother-Sother*. U3 then adds a link while speaking: *Link-Add-Tsame-Sauthor*. Actions with no utterances in parallel have the keyword *NoSpeech* (e.g. item action 6).

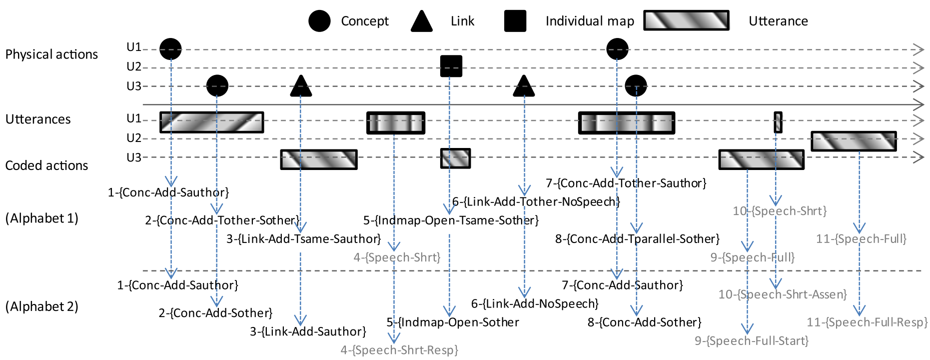

Fig. 6 Example of an excerpt of a group's events using alphabets 1 and 2. Vertical arrows associate each event with the resulting encoded item actions

Utterances with no physical actions in parallel are encoded like item actions 4, 9, 10 and 11 (*Speech-Shrt*/*Full*). Item action 8 illustrates a case where two physical actions were performed in parallel (*Tparallel*).

Alphabet 2 focuses on the detailed description of the verbal participation in context with the physical actions. Following the same rationale described above, this alphabet introduces information about the length, order and authorship of verbal utterances where there are no physical actions in parallel. Figure 6 shows an example of the encoding of the same actions for Alphabet 2. It introduces three keywords (Table 5, Alphabet 2, Level 3). These are: *Start* (e.g. Fig. 6, item action 9), when a utterance has no other utterance immediately before it; *Resp* (response), when a utterance immediately follows a previous utterance by another learner (e.g. item actions 4 and 11); and *Assen* (assenting), for short utterances (1 to 2 s long) that occur while another learner speaks (e.g., item action 10). We used these rules to automatically code all the utterances. We compared this rule-based tagging with a human tagging in a 10 % of the dataset and we found 76 % of agreement in identifying learners' verbal responses. The alphabet also keeps the keywords associated with speech to encode physical actions (NoSpeech, Sauthor and Sother).

Alphabet 3 captures the *interaction of students with others' objects.* This alphabet considers contextual information about the actions that are performed by learners, either on the objects they initially created, or the ones created by others. This is achieved by the keywords *Owner* and *Difowner* respectively (Table 5, Alphabet 3, Level 4). The alphabet also keeps the keywords associated with speech to encode physical actions (NoSpeech, Sauthor and Sother), but it does not include independent utterances. To keep the alphabets as simple as possible but, at the same time, to capture the essential aspects of interactivity on others students' objects, this alphabet does not differentiate among types of objects (only 1 keyword *Obj* for Level 1).

Alphabet 4 targets the research question that explores the *influence of the access to knowledge structures.* This alphabet keeps the keywords associated with speech in Level 3 as in Alphabet 2, and adds information provided by the keywords *Pers* and *NoPers* in Level 4. *Pers* is associated to actions performed on concepts or links that were contained in a *personal/*individual map while this is being displayed on the tabletop (as in Fig. 3, left) or immediately before. *Nopers* corresponds to the rest of the actions on concepts and links, those that are not in any individual map displayed on the tabletop. The objective of this alphabet is to find possible differences in the actions performed *after* learners *open* their individual maps (*Indmap*).

The algorithm: Differential sequence mining

As a result of encoding the groups' actions, according to the four alphabets described above, we obtained four datasets of encoded item actions with two sub-sets of data each. Each sub-set contains 10 long sequences of item actions for either a high or low collaboration groups. In order to extract patterns of activity we applied the *differential sequence mining* technique (DSM) developed by Kinnebrew et al. (2012), which looks for sequential patterns that differentiate two datasets.

A sequential pattern is a consecutive or non consecutive ordered sub-set of a sequence of events that is considered frequent when it meets a minimum *support* criteria (Jiang and Hamilton 2003). For the DSM technique this is called sequence-support (*s-support*) that corresponds to the number of sequences in which the pattern occurs, regardless of how frequently it repeats within each sequence. We set the minimum threshold to consider a pattern as frequent if this was present in at least half of the sequences (*s-support* = 0.5) following previous work by Kinnebrew et al. (2012). The algorithm also calculates consecutive and repeated patterns within the dataset of sequences. This is called instance support (*i-support*). We set the maximum error threshold to 1 to allow the matching of patterns with sub-sequences if there was an edit distance of 0 (perfect match) or 1 (one different action in the sub-sequence) between them. This has the impact of allowing a larger number of sequences to be considered as *differential* even if the matching is not perfect. This has proved effective in matching similar sequences of actions in learning environments (Kinnebrew et al. 2012; Martinez-Maldonado et al. 2011c). The output of this algorithm is a list of frequent patterns that meet the minimum support in each dataset and that distinguish more collaborative from less collaborative groups ($p<0.1$) also following previous work by Kinnebrew et al. (2012). Next, we present the results of running the algorithm for each research question.

Results

Question 1: Can we distinguish more collaborative from less collaborative groups by the interwoven stream of students' verbal and physical participation? After applying the DSM algorithm on Alphabet 1, we selected the patterns whose i-support distinguished high from low groups with a confidence of at least 90 % ($p<=0.10$) and that were composed of at least two item actions (e.g. {Conc-Add-Tother-Sother} > {Speech-Shrt}).

We obtained 261 differential patterns. Table 6 shows the top-4 most differential patterns that were found in each sub-set for each phase. For the brainstorming phase, the patterns A, B, C, and D are very similar. All are patterns where students added (Add) and arranged (Mov) concepts without speaking (NoSpeech) and with some degree of parallelism and concurrency (Tparallel and Tother keywords respectively; found in A, B and C). By contrast, the more collaborative groups displayed a different strategy by interleaving periods of just verbal activity (Speech) with physical actions that were accompanied by other students' talk (Sother in patterns E, F, G and H).

To summarize the rest of the patterns that were found, Table 7 shows the frequency of appearance of keywords in patterns that met the differential criteria ($p<=0.1$). Confirming the trends suggested by the examples (Table 6), for *brainstorming,* the main difference was that high collaboration groups had more patterns in two main classes: ones with speech and no actions in parallel; ones with speech while other students performed actions (*Speech* and *Sother* appeared in 93 % and 43 % of the frequent sequences for the high collaboration groups against 50 % and 18 % of the less collaborative groups).

For the *linking* phase, a similar trend remained. The low collaboration groups had an increased presence of parallelism in their actions (*Tparallel* = 36 % for low against 3 % for high groups) as in the patterns I, K and L. Additionally, more than 65 % of the low collaboration groups' actions were not accompanied by speech (*NoSpeech* >60 % for low and <10 % for high groups). High collaboration groups showed patterns of sequenced speech in the linking phase (patterns O and P).

This alphabet enabled us to discover that learners tend to not talk while touching the tabletop (*Sauthor* keyword is not present in the top patterns of Table 6, and in Table 7, the second last column (*Sauthor*) shows very low occurrence). There is evidence that a strategy followed by the more collaborative groups involved maintaining high levels of both speech

Table 6 Top sequential patterns found using Alphabet 1. Repetitive keywords and descriptions in bold letters

		Top-4 most differential patterns	Description
Brainstorming	Low collab.	A=Con-Mov-Tsame-Mult-**NoSpeech** > Con-Add-**Tparallel-NoSpeech**	Actions in parallel **with no speech**
		B=Con-Add-Tother-NoSpeech > Con-Add-Tother-**Sother**	Actions on others' objects with others' speech
		C=Con-Add-Tother-**NoSpeech** > Con-Add-**Tparallel-NoSpeech**	Actions in parallel **with no speech**
		D=Con-Mov-Tsame-Mult-**NoSpeech** > Con-Mov-Tsame-**NoSpeech** > Con-Mov-Tsame-**NoSpeech**	Actions on own objects **with no speech**
	High collab.	E=Speech-Shrt > Con-Add-Tsame-**Sother** > Con-Mov-Tsame-**Sother**	Speech and actions on own objects with **other's speech**
		F=Speech-Shrt > Con-Mov-Tsame-Mult-**Sother** > Con-Mov-**Tparallel-Sother**	Speech and actions in parallel with **other's speech**
		G=Speech-Full > Speech-Shrt > Con-Mov-Tsame-**Sother**	Speech and actions on own objects with **others' speech**
		H=Con-Mov-Tsame-Mult-**Sother** > Con-Mov-**Tparallel-Sother**	Actions in parallel with **other's speech**
Linking	Low collab.	I=Con-Mov-Tsame-Mult-NoSpeech > Con-Mov-**Tparallel-NoSpeech** > Link-Mov-Tother-**NoSpeech**	Actions in parallel **with no speech**
		J=Speech-Shrt > Con-Mov-Tsame-Mult-**NoSpeech** > Con-Mov-**Tparallel-NoSpeech**	Speech and actions in parallel **with no speech**
		K=Link-Add-Tsame-**NoSpeech**>Link-Mov-Tsame-**NoSpeech**> Link-Mov-Tother-**NoSpeech**	Actions on own objects **with no speech**
		L=Con-Mov-**Tparallel**-NoSpeech > Link-Add-Tsame-**NoSpeech** > Speech-Shrt	Speech and actions in parallel **with no speech**
	High collab.	M=Con-Mov-Tother-**Sother** > Link-Mov-Tsame-**Sother** > Speech-Shrt	Speech and actions in own objects with **other's speech**
		N=Speech-Full > Con-Mov-Tsame-Mult-**Sother** > Con-Mov-**Tparallel-Sother**	Speech and actions in parallel with **other's speech**
		O=Speech-Full > Speech-Full > Speech-Full > Con-Mov-Tsame-Mult-NoSpeech	**Sequenced** utterances and multiple actions
		P=Speech-Shrt > Con-Mov-Tsame-Mult-**Sother** > Speech-Shrt > Speech-Shrt>Speech-Full>Speech-Shrt>Speech-Shrt	**Sequenced** utterances and multiple actions

p<=0.05

Table 7 Proportions of keywords in frequent patterns by using Alphabet 1

	Collaboration	Speech	Tother	Tsame	Tparallel	Nospeech	Sauthor	Sother
Phase 1 (brainstorming)	Low	50 %	**50 %**	25 %	18 %	**62 %**	0 %	18 %
	High	**93 %**	**10 %**	39 %	16 %	**7 %**	5 %	**43 %**
Phase 2 (linking)	Low	45 %	**32 %**	53 %	**36 %**	**65 %**	2 %	11 %
	High	**92 %**	**4 %**	31 %	3 %	**10 %**	0 %	24 %

p-value<=0.1

levels and turn taking, accompanied by some physical actions, (Table 6, pattern P) and keeping parallelism low. By contrast, the less collaborative groups had higher levels of physical activity with just a few unchained verbal interventions (see patterns J and L).

Question 2: Can we distinguish more collaborative from less collaborative groups by extracting patterns of interaction based on just students' verbal participation? Pattern P in Table 6 exemplifies the patterns that need deeper exploration analysis (sequenced utterances). Alphabet 2 was designed to provide more information for these verbal patterns. We obtained 225 differential patterns using Alphabet 2.

Table 8 shows that most of the less collaborative groups' sequences include actions performed on concepts and links with no speech in parallel both in brainstorming (patterns A to D) and even more frequently in the linking phase (patterns J, K and L). Additionally, patterns show that some utterances were not followed by any response (patterns A, C, D and I with keyword Speech-Start).

By contrast, high collaboration groups tended to combine physical actions performed with speech from the same author or other learners (*Sauthor*-*Sother)*; and sequences of utterances that can be associated with conversation patterns (patterns G and M). Another trend found is the keyword *Start* followed by a *Resp*onse, or at least some verbal reaction in both phases of the activity (patterns E, F, N and O). Pattern H shows that in the brainstorming phase, these students tend to open their individual maps and follow this action with long speech activity. A similar pattern in these high collaboration groups was found for the linking phase, with the difference that, the speech was accompanied by physical actions (see pattern P). It is not clear how they interacted with these individual maps hence the need of further exploration that is formulated in our Research Question 4.

Table 9 shows the proportion of keywords in the rest of the patterns that met the differential criteria. The presence of verbal utterances, and especially, responses to other students, distinguished high from less collaborative groups in both phases (60 % and 45 % of the patterns in high groups had at least one responding utterance (*Resp*) respectively, in contrast to just 12 % and 8 % of patterns for the corresponding phases in the low groups). Short assenting verbal utterances by learners, while another learner was speaking, were more common in more collaborative groups (*Assen*=25 % for high and 13 % for low collaboration). This confirms the differences suggested in the examples described above.

Question 3: Can we distinguish more collaborative from less collaborative groups based on patterns involving traces of interaction of students with others' objects? After running the DSM algorithm using Alphabet 3 we obtained a total of 174 patterns. Table 10 presents the

Table 8 Top sequential patterns found using Alphabet 2

		Top-4 most differential patterns	Description
Brainstorming	Low collab.	A= Con-Add-**NoSpeech** > Con-Add-**NoSpeech** > **Speech**-Shrt- **Start** > Con-Add-**NoSpeech**	Start utterance, no response, actions **with no speech**
		B=Con-Mov-**NoSpeech** > Con-Add-**NoSpeech** > Con-Add-**NoSpeech** > Con-Add-**NoSpeech** >Con-Add-**NoSpeech**	Actions **with no speech**
		C= Con-Add-**NoSpeech** > Con-Add-**NoSpeech** > Con-Add-**NoSpeech** > **Speech**-Shrt-**Start** > Con-Add-**NoSpeech**	Start utterance, no response, actions **with no speech**
		D= Con-Add-**NoSpeech** > **Speech**-Shrt-**Start** > Con-Add-**NoSpeech**	Start utterance, no response, actions **with no speech**
	High collab.	E=Con-Mov-Sother > Con-Mov-Sauthor > **Speech**-Shrt-**Resp**	Actions with speech and speech by others with **response**
		F= Con-Mov-Sother > **Speech**-Shrt-**Resp** > **Speech**-Shrt-Assen	Action with speech by others with **response**
		G= **Speech**-Full-**Resp** > **Speech**-Shrt-**Resp** > **Speech**-Shrt-**Resp** > **Speech**-Full-**Resp**	Conversation
		H= Indmap-Open-Sother > **Speech**-Full-**Start**	Open map and speech
Linking	Low collab.	I= **Speech**-Shrt-**Start** > **Speech**-Shrt-**Resp**> Con-Mov-Mult-**NoSpeech**> **Speech**-Shrt-**Start**	Start utterance, with short response
		J= Link-Add-**NoSpeech** > Con-Mov-**NoSpeech** > Link-Mov-Mult-**NoSpeech** > Con-Mov-**NoSpeech**	Actions **with no speech**
		K= Link-Add-**NoSpeech** > Con-Mov-**NoSpeech** > Link-Rem-**NoSpeech** > Con-Mov-Mult-**NoSpeech**	Actions **with no speech**
		L= Link-Mov-**NoSpeech** > Link-Rem-**NoSpeech** > Con-Mov-**NoSpeech** > Link-Add-**NoSpeech**	Actions **with no speech**
	High collab.	M= **Speech**-Shrt-**Resp** > **Speech**-Shrt-**Resp** > **Speech**-Full-**Start** > **Speech**-Shrt-Assen	Conversation
		N= Con-Mov-Sother > **Speech**-Shrt-**Start** > **Speech**-Full-**Resp**	Action with speech by others with **response**
		O= Con-Mov-Sother > **Speech**-Shrt-Assen > Con-Mov-Sauthor	Actions with speech and speech by others with **response**
		P = **Speech**-Shrt-Assen > Indmap-Mov-Sother > Con-Mov-Sother	Speech, Open map and actions with speech

p<=0.05

Table 9 Proportions of keywords in frequent patterns by using Alphabet 2

	Collaboration	*Speech*	*Start*	*Resp*	*Assen*	*Nospeech*	*Sauthor*	*Sother*
Phase 1 (brainstorming)	Low	27 %	14 %	12 %	10 %	**77 %**	2 %	**14 %**
	High	**83 %**	**43 %**	**60 %**	25 %	10 %	6 %	43 %
Phase 2 (linking)	Low	12 %	**7 %**	8 %	1 %	**94 %**	2 %	8 %
	High	**59 %**	45 %	**45 %**	13 %	39 %	2 %	19 %

$p<=0.1$

top differential patterns. It shows that the main distinction, for ownership and interaction, was not between high and low collaborative groups but between phases.

These patterns suggest that most of the groups performed actions on their own objects during the brainstorming, without interacting with others' objects (no *Difowner* keyword in patterns from A to G). Only one of the top patterns shows that members of high collaboration groups also interacted with others' objects to some extent (pattern H).

In line with previous findings, the speech also marked a difference between high and low collaboration groups (patterns F, G and H). For the *linking* phase we can see a prevalence presence of actions performed on objects created by others (*Difowner* keyword in most of the patterns in the linking phase). The more collaborative groups presented strategies of interaction with others' objects to a lesser degree, combining interaction of students on their own objects with speech by the same learner or others'.

Table 11 shows the proportion of keywords for the rest of the patterns. Both high and low groups had fewer physical interaction with others' elements during the brainstorming, similarly to the example patterns (14 % and 3 % for *Difowner* respectively). Indeed, the low collaborative groups always performed actions on their own objects (100 % for the keyword *Owner*).

The above suggests that the strategy of splitting the work, without verbally communicating with other members, is what most distinguished the low collaborative groups in the brainstorming phase. For the linking phase the patterns of the low groups had a higher level of interaction with others' objects (*Difowner* =83 %). However, patterns for the high collaboration group also had high rates of interaction with others' objects (*Difowner* =62 %) in additional to patterns of speech.

Question 4: Can we distinguish more collaborative from less collaborative groups in terms of the actions that follow the access to others' knowledge structures? To investigate the actions learners performed in association with accessing learners' maps, the analysis to address question 4 was different from the previous questions. Here, we only considered the actions that occurred while each individual concept map remained open. The statistics show a difference in the number of times groups' accessed individual maps (145 for high and 102 for low groups); therefore, we expect to find more patterns in the high collaboration groups.

Table 12 shows the differential sequences for both groups. For the *brainstorming* phase, the less collaborative groups did not have any differential patterns meeting the *support* condition. By contrast, patterns for the more collaborative groups had increased levels of conversation after students accessed their individual maps (see patterns B, C and E). Patterns also show evidence that students took turns to open and explore individual maps one after the other (*Open* and *Close* events in patterns A, D and E). For the *linking* phase, the less

Table 10 Top sequential patterns found using Alphabet 3

		Top-4 most differential patterns	Description
Brainstorming	Low collab.	A= Obj-Mov-Owner-NoSpeech>Obj-Mov-Owner-NoSpeech > Obj-Mov-Owner-Mult-NoSpeech>Obj-Mov-Owner-Mult-NoSpeech	Actions on **own** objects, **no speech**
		B= Obj-Add-Owner-Sother > Obj-Add-Owner-NoSpeech > Obj-Add-Owner-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on **own** objects, **some speech**
		C= Obj-Add-Owner-NoSpeech > Obj-Add-Owner-NoSpeech > Obj-Mov-Owner-NoSpeech> Obj-Add-Owner-NoSpeech >	Actions on **own** objects, **no speech**
		D= Obj-Mov-Owner-Mult-NoSpeech > Obj-Mov-Owner-NoSpeech > Obj-Mov-Owner-Mult-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on **own** objects, **no speech**
	High collab.	E= Obj-Mov-Owner-Sother > Obj-Mov-Owner-NoSpeech > Obj-Mov-Owner-Mult-Sother	Actions on **own** objects, **no speech**
		F= Obj-Add-Owner-Sother > Obj-Mov-Owner-Mult-Sother > Obj-Add-Owner-Sother	Actions on **own** objects, **others' speech**
		G= Obj-Add-Owner-Sother > Obj-Rem-Owner-Sother > Obj-Add-Owner-Sother > Obj-Add-Owner-Sother	Actions on **own** objects, **others' speech**
		H= Obj-Mov-Owner-Mult-Sauthor > Obj-Mov-**Difowner**-Sother > Obj-Mov-Owner-Sother	Actions on others' objects, **others' speech**
Linking	Low collab.	I= Obj-Add-Owner-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Add-Owner-NoSpeech >	Actions on others' objects, **no speech**
		J= Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on others' objects, **no speech**
		K= Obj-Mov-**Difowner**-Mult-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on others' objects, **no speech**
		L= Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on others' objects, **no speech**
	High collab.	M= Obj-Mov-Owner-Sauthor > Obj-Mov-Owner-Sother > Obj-Mov-**Difowner**-Sother	Actions on others' objects, **own and others' speech**
		N= Obj-Mov-**Difowner**-Sother > Obj-Mov-**Difowner**-Sother > Obj-Add-Owner-Sother	Actions on others' objects, **others' speech**
		O= Obj-Add-Owner-Sother > Obj-Mov-Owner-Sother > Obj-Mov-Owner-Mult-NoSpeech	Actions on own objects, **others' speech**
		P= Obj-Mov-**Difowner**-Mult-NoSpeech > Obj-Mov-**Difowner**-Mult-NoSpeech > Obj-Chg-**Difowner**-NoSpeech	Actions on others' objects, **no speech**

p<=0.05

Table 11 Proportions of keywords in frequent patterns by using Alphabet 3

	Collaboration	*Owner*	*Difowner*	*NoSpeech*	*Sauthor*	*Sother*
Phase 1 (brainstorming)	Low	100 %	**3 %**	94 %	1 %	1 %
	High	56 %	**14 %**	25 %	22 %	97 %
Phase 2 nnlinking)	Low	95 %	62 %	66 %	27 %	40 %
	High	97 %	**83 %**	99 %	0 %	4 %

$p <= 0.1$

collaborative groups had some patterns; however, unlike the dominant strategy followed by the more collaborative groups, these were mostly physical actions (*Mov*e actions) without verbal interaction after accessing individual maps (*NoSpeech* keyword in the patterns F to I). In the *linking* phase, the higher collaboration groups continued using the individual maps as a tool to drive verbal communication (pattern K) and they opened more than one individual map at the same time, possibly for comparison (pattern M).

Against our expectations, the length of the patterns we found was not enough to detect *add* events for concepts and links contained in those accessed individual maps. The keyword *Pers* was found in some patterns (H and L but this corresponded to *move* actions.

Discussion and conclusions

In this paper, we presented an approach to explore whether we could automatically distinguish how and low collaboration groups, by exploiting the affordances of an enriched tabletop, with its learning environment that can keep track of students' physical and verbal activity. Our empirical study showed considerable promise for obtaining indicators of collaborative work.

We envisage that our work provides a foundation for creating a system with three components:

- the *data capture* system to track and gather data of group activity;
- the *data analytics* component, which is based on careful design of the alphabets that are a basis for producing group indicators via statistical and data mining techniques;
- and the *data presentation* component that aims to present to teachers, researchers or students with visual information or knowledge about the collaborative process but which implementation goes beyond the scope of this paper.

We have implemented the technological infrastructure to automatically and unobtrusively capture and integrate both verbal and physical students' interactions in the tabletop (Martinez-Maldonado et al. 2011a). The analysis technique, based on the design of alphabets, combines the integration of verbal and physical interactions, with the use of sequence mining in order to find patterns that can distinguish groups that worked either more collaboratively or less collaboratively. This analysis proved effective in addressing our four research questions regarding patterns that differentiate groups in interactive tabletops.

The *statistical exploration* of several indicators of interaction suggested that there were differences in groups' interactions based on their level of collaboration. However, such aggregating information at the end of the group activity has proven to have serious limitations. First, the statistical differences between the measures for the high or low collaboration groups

Table 12 Top sequential patterns found using Alphabet 4

		Top 4 most differential patterns	Description
Brainstorming	High collab.	A=Indmap-Close>Indmap-Open>**Speech**-Shrt	Speech after opening map, taking turns
		B=Indmap-Open>**Speech**-Full>**Speech**-Shrt>**Speech**-Shrt>**Speech**-Shrt	Speech after opening map
		C=Indmap-Open>**Speech**-Full	Speech after opening map
		D=**Speech**-Shrt>Indmap-Mov-Sother>Indmap-Close>Indmap-Open	Speech and open map, taking turns
		E=Indmap-Mov-Mult-Sother>Indmap-Close>Indmap-Open>**Speech**-Shrt	Speech after open map, taking turns
Linking	Low collab.	F=Indmap-Close > Indmap-Open > Indmap-Mov-Mult-NoSpeech > Indmap-Mov-NoSpeech	Opening map, **no speech**
		G=Indmap-Mov-Mult-NoSpeech > Indmap-Mov-NoSpeech > Indmap-Mov-Mult-NoSpeech	Move maps, **no speech**
		H=Indmap-Mov-NoSpeech > Con-Mov-NoSpeech-Pers > Con-Mov-NoSpeech-Pers	Move maps, **no speech**
		I=Indmap-Open>Indmap-Mov-Mult-NoSpeech> Indmap-Mov-NoSpeech> Indmap-Mov-NoSpeech	Opening map, **no speech**
	High collab.	J=Indmap-Open > Indmap-Close > Indmap-Open > Indmap-Mov-NoSpeech	Opening maps one by one
		K=Indmap-Open > **Speech**-Shrt > **Speech**-Shrt	Speech after opening map
		L=Indmap-Open > Con-Mov-NoSpeech-Pers	Open map and action
		M=Indmap-Open > Indmap-Mov-NoSpeech > **Indmap-Open**	Open more than one map in parallel

$P <= 0.05$

were not significant. So they were not powerful enough to capture the differences. In addition, since they were only available at the end of the session, they would not be a useful basis for informing a teacher of potential problem groups during a class.

We then reported our approach to analyze students' actions at a fine-grained level taking account of the order of actions and the interplay between the differentiated actions of each group member. The DSM technique, along with the four alphabets, adds contextual information to the sequence of actions and this enabled us to find patterns of verbal participation, parallelism, concurrency, linkage between verbal and physical actions, access to individual knowledge representations and students' actions on others' digital objects.

First, by applying Alphabet 1, we discovered that the less collaborative groups had a predomination of patterns with physical interactions, high levels of physical concurrency and greater parallelism than the more collaborative groups. By contrast, the more collaborative groups had more verbal discussions in conjunction with physical actions, especially in the *brainstorming* phase. They also showed less concurrency in the physical dimension and less parallelism. This seems consistent with these students being more aware of their peers' actions and also making use of group discussions about the actions performed on the group map.

Second, we explored in more detail the patterns of *verbal participation* through the Alphabet 2. One of the most interesting findings for the less collaborative groups was the detection of patterns where a learner spoke briefly without getting response from other students. This aspect of communication was also considered by Meier et al. (2007), under the dimension of mutual understanding. For groups to maintain mutual understanding, they needed to provide verbal feedback on their understanding in the form of an appropriate response, or by asking for clarification. In line with this, the more collaborative groups had higher rates of responses after other learners had spoken. These groups also had patterns of physical actions accompanied by speech by other learners. This is also consistent with these students being more aware of others' actions and discussing each others' actions.

Third, the findings from applying Alphabet 3 to inspect interactions of students with others' objects partly contradicted the analysis carried out by Martinez-Maldonado et al. (2012b). We found that the more collaborative groups had some interaction with others' objects in the *brainstorming* phase but in the *linking* phase, the less collaborative groups interacted more with others' objects.

Fourth, we explored the patterns of actions that occurred after students opened their individual concept maps to share them with others or to recall what they had done in the initial private mapping activity (Alphabet 4). We found evidence that suggests that the more collaborative groups accessed their individual maps to trigger discussion. Their actions showed that they either opened one map after another, or opened at least two concept maps simultaneously for possible comparison. For the less collaborative groups, our data does not really show how they used their individual maps. Contrary to what we had expected, the patterns found did not show the addition of concepts or propositions from those maps. This may be explored further by refining the alphabet.

The patterns we discovered are important at multiple levels. First, they demonstrate that we have achieved our overall goal to exploit the digital footprints of learners in the tabletop. Importantly, this work provides a foundation for creating interfaces for bringing the collaboration quality to the attention of the stakeholders. This includes learners in the groups. It has the potential to be particularly valuable for teachers who need to manage several groups in a classroom. It also provides researcher insights more broadly. Overall, the indicators of physical activity and verbal participation, produced by the implementation of our approach, are modest, if not limited, when compared with a full qualitative analysis of the utterances that can be carried out by an expert human observer. However, we argue that our study provides evidence that our approach can serve as a basis for a further development of automatic supporting systems for students or monitoring tools for their teachers. We designed each alphabet to correspond to the elements of a specific research question and therefore, each provides different information. This range of insights about collaboration cannot be obtained through a single alphabet that simply aggregates all the keywords. This would only lead to very long item actions. It would be harder to interpret, and more difficult for the algorithm to discover patterns, given the higher variability of contextual information that would have to be analyzed at once. The formulation of other questions requires different, new alphabets. The current work provides as basis for creating these.

Finally, the approach itself can serve as a basis for the design of interactive tabletop systems for collaborative learning, enabling a new level of support. We envisage systems that can capture, analyze and present students' information in order to enhance awareness for teachers, researchers or back to the students themselves. Real time visualizations of the group process can be designed for the teacher, either exclusively or shared with the students. For example patterns found can be used as a benchmark to compare against new groups' patterns. If we detect patterns associated with non collaborative strategies, the system can trigger an alarm in real time to help teachers to enhance their awareness and possibly help them make more informed decisions about when to intervene with particular groups.

References

AlAgha, I., Hatch, A., Ma, L., & Burd, L. (2010). Towards a teacher-centric approach for multi-touch surfaces in classrooms. In *Proceedings of the International Conference on Interactive Tabletops and Surfaces 2010 (ITS 2010)* (pp. 187–196). New York: ACM.

Al-Qaraghuli, A., Zaman, H., Olivier, P., Kharrufa, A., & Ahmad, A. (2011). Analysing Tabletop Based Computer Supported Collaborative Learning Data through Visualization. In *Proceedings of the Visual Informatics 2011 (IVIC 2011)* (pp. 329–340). Berlin: Springer.

Anaya, A., & Boticario, J. (2009). Clustering learners according to their collaboration. In *Proceedings of the Computer Supported Cooperative Work in Design (CSCWD 2009)* (pp. 540–545). Washington: IEEE.

Anaya, A., & Boticario, J. (2011). Application of machine learning techniques to analyse student interactions and improve the collaboration process. *Expert Systems with Applications, 38*(2), 1171–1181.

Baker, R. S., & Yacef, K. (2009). The State of Educational Data Mining in 2009: A Review and Future Visions. *Journal of Educational Data Mining (JEDM), 1*(1), 3–17.

Baraldi, S., DelBimbo, A., & Valli, A. (2006). Bringing the Wiki Collaboration Model to the Tabletop World. In *Proceedings of the IEEE International Conference on Multimedia and Expo 2006 (ICME 2006)* (pp. 333–336). Washington: IEEE.

Cañas, A. J., & Novak, J. D. (2008). Next step: Consolidating the cmappers community. In *Proceedings of the 3rd International Conference on Concept Mapping 2008 (CMC 2008)* (pp. 532–539). Tallinn: OÜ Vali Press

Dillenbourg, P. (1998). What do you mean by 'collaborative learning'? In *Collaborative Learning: Cognitive and Computational Approaches. Advances in Learning and Instruction Series* (pp. 1–19). Oxford: Elsevier Science.

Dillenbourg, P., & Jermann, P. (2010). Technology for classroom orchestration. In *New science of learning* (pp. 525–552). New York: Springer.

Dillenbourg, P., Zufferey, G., Alavi, H., Jermann, P., Do-Lenh, S., & Bonnard, Q. (2011). Classroom orchestration: The third circle of usability. In *Proceedings of the International Conference on Computer Supported Collaborative Learning 2011 (CSCL 2011)* (pp. 510–517). ISLS.

Dimitracopoulou, A., Mones, A., Dimitriadis, Y., Morch, A., Ludvigsen, S., & Harrer, A. (2004). State of the art on interaction analysis: Interaction analysis indicators. 1–148 Available online: http://ltee.org/adimitr/?page_id=64.

Dimitrakopoulou, A., Petrou, A., Martinez, A., Marcos, J. A., Kollias, V., Jermann, et al. (2006). State of the art of interaction analysis for Metacognitive Support and Diagnosis. 1–119. *Deliverable D.31.1*. Available online: http://ltee.org/adimitr/?page_id=64.

Do-Lenh, S., Kaplan, F., & Dillenbourg, P. (2009). Paper-based concept map: The effects of tabletop on an expressive collaborative learning task. In *Proceedings of the British Computer Society Conference on Human-Computer Interaction 2009 (BCH HCI 2009)* (pp. 149–158). Cambridge: British Computer Society.

Engelmann, T., & Hesse, F. (2010). How digital concept maps about the collaborators' knowledge and information influence computer-supported collaborative problem solving. *International Journal of Computer-Supported Collaborative Learning, 5*(3), 299–319.

Falcao, T. P., & Price, S. (2009). What have you done! the role of 'interference' in tangible environments for supporting collaborative learning. In *Proceedings of the 9th International Conference on Computer Supported Sollaborative Learning (CSCL 2009)* (pp. 325–334). ISLS.

Felder, R. M., & Brent, R. (1994). *Cooperative Learning in Technical Courses: Procedures, Pitfalls, and Payoffs*. Raleigh: North Carolina State University.

Fleck, R., Rogers, Y., Yuill, N., Marshall, P., Carr, A., Rick, J., et al.. (2009). Actions Speak Loudly with Words: Unpacking Collaboration Around the Table. In *Proceedings of the International Conference on Interactive Tabletops and Surfaces 2009 (ITS 2009)* (pp. 189–196). New York: ACM.

Gao, H., Shen, E., Losh, S., & Turner, J. (2007). A review of studies on collaborative concept mapping: What have we learned about the technique and what is next? *Journal of Interactive Learning Research, 18*(4), 479–492.

Harrer, A., Martínez-Monès, A., & Dimitracopoulou, A. (2009). Users' data: Collaborative and social analysis. In *Technology-Enhanced Learning* (pp. 175–193). Netherlands: Springer.

Harris, A., Rick, J., Bonnett, V., Yuill, N., Fleck, R., Marshall, P., & Rogers, Y. (2009). Around the table: Are multiple-touch surfaces better than single-touch for children's collaborative interactions? In *Proceedings of the 9th International Conference on Computer Supported Collaborative Learning (CSCL 2009)* (pp. 335–344). ISLS.

Hilliges, O., Butz, A., Izadi, S., Wilson, A. D., & 221. (2010). Bringing the Physical to the Digital. In *Tabletops - Horizontal Interactive Displays* (p. 189). London: Springer.

Jeong, H., & Hmelo-Silver, C. E. (2010). An Overview of CSCL Methodologies. In *Proceedings of the 9th International Conference of the Learning Sciences (ICLS 2010)* (pp. 920–921). ISLS.

Jermann, P., Zufferey, G., Schneider, B., Lucci, A., Lepine, S., & Dillenbourg, P. (2009). Physical space and division of labor around a tabletop tangible simulation. In *Proceedings of the 9th International Conference on Computer Supported Collaborative Learning (CSCL 2009)* (pp. 345–349). ISLS.

Jiang, L., & Hamilton, H. (2003). Methods for Mining Frequent Sequential Patterns. In *Advances in Artificial Intelligence* (Vol. 2671, p. 992). Berlin: Springer.

Johnson, R. T., & Johnson, D. W. (1986). Action research: Cooperative learning in the science classroom. *Science and Children, 24*(2), 31–32.

Johnson, D. M., Sutton, P., & Poon, J. (2000). Face-to-Face vs. CMC: Student communication in a technologically rich learning environment. In *Proceedings of the 17th Annual Conference of the Australian Society for Computers in Learning in Tertiary Education (ASCILITE 2000)* (pp. 509–520). Lismore: Southern Cross University Press.

Kharrufa, A. S. (2010). *Digital tabletops and collaborative learning.* Doctoral Dissertation, Newcastle University. (EThOS Persistent ID: uk.bl.ethos.525036).

Kinnebrew, J. S., Loretz, K. M., & Biswas, G. (2012). A contextualized, differential sequence mining method to derive students' learning behavior patterns. *Journal of Educational Data Mining (JEDM), 5*(1), 190–219.

Kirschner, P. A. (2001). Using integrated electronic environments for collaborative teaching/learning. *Learning and Instruction, 10*(1), 1–9.

Kreijns, K., Kirschner, P. A., & Jochems, W. (2003). Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: A review of the research. *Computers in Human Behavior, 19*(3), 335–353.

Leonard, S., Mary Elizabeth, S., & Samuel, S. D. (1997). Effects of small-group learning on undergraduates in science, mathematics, engineering, and technology. *Review of Educational Research, 69*(1), 21–51.

Marshall, P., Hornecker, E., Morris, R., Sheep Dalton, N., & Rogers, Y. (2008). When the fingers do the talking: A study of group participation with varying constraints to a tabletop interface. In *Proceedings of the Horizontal Interactive Human Computer Systems, 2008 (TABLETOP 2008).* (pp. 33–40). Washington: IEEE.

Martinez-Maldonado, R., Kay, J., & Yacef, K. (2010). Collaborative concept mapping at the tabletop. In *Proceedings of the International Conference on Interactive Tabletops and Surfaces (ITS 2010)* (pp. 207–210). New York: ACM.

Martinez-Maldonado, R., Collins, A., Kay, J., & Yacef, K. (2011a). Who did what? who said that? Collaid: An environment for capturing traces of collaborative learning at the tabletop. In *Proceedings of the International Conference on Interactive Tabletops and Surfaces (ITS2011)* (pp. 172–181). New York: ACM.

Martinez-Maldonado, R., Kay, J., Wallace, J., & Yacef, K. (2011b). Modelling symmetry of activity as an indicator of collocated group collaboration. In *Proceedings of the International Conference on User Modeling, Adaptation and Personalization (UMAP 2011)* (pp. 196–204). Berlin: Springer.

Martinez-Maldonado, R., Yacef, K., Kay, J., Kharrufa, A., & Al-Qaraghuli, A. (2011c). Analysing frequent sequential patterns of collaborative learning activity around an interactive tabletop. In *Proceedings of the International Conference on Educational Data Mining 2011 (EDM 2011)* (pp. 111–120). IEDMS.

Martinez-Maldonado, R., Dimitriadis, Y., Kay, J., Yacef, K., & Edbauer, M.-T. (2012a). Orchestrating a multi-tabletop classroom: From activity design to enactment and reflection. In *Proceedings of the International Conference on Interactive Tabletops and Surfaces (ITS 2012)* (pp. 119–128). 2396655: New York: ACM.

Martinez-Maldonado, R., Yacef, K., Kay, J., & Schwendimann, B. (2012b). An interactive teacher's dashboard for monitoring multiple groups in a multi-tabletop learning environment. In *Proceedings of the International Conference on Intelligent Tutoring Systems 2012 (ITS 2012)* (pp. 482–492). Berlin: Springer.

Martinez-Maldonado, R., Yacef, K., Kay, J., & Schwendimann, B. (2012c). Unpacking traces of collaboration from multimodal data of collaborative concept mapping at a tabletop. In *Proceedings of the International Conference of the Learning Sciences 2012 (ICLS 2012)* (pp. 241–245). ISLS.

Martinez-Maldonado, R., Kay, J., & Yacef, K. (2013). An automatic approach for mining patterns of collaboration around an interactive tabletop. In *Proceedings of the International Conference on Artificial Intelligence in Education 2013 (AIED 2013)* (pp. 101–110). Berlin: Springer.

Meier, A., Spada, H., & Rummel, N. (2007). A rating scheme for assessing the quality of computer-supported collaboration processes. *International Journal of Computer-Supported Collaborative Learning, 2*(1), 63–86.

Mercier, E., Higgins, S., Burd, E., & Joyce-Gibbons, A. (2012). Multi-Touch Technology to Support Multiple Levels of Collaborative Learning in the Classroom. In *Proceedings of the International Conference of the Learning Sciences 2012 (ICLS 2012)* (pp. 187–191). ISLS.

Molinari, G., Sangin, M., Nüssli, M.-A., & Dillenbourg, P. (2008). Effects of knowledge interdependence with the partner on visual and action transactivity in collaborative concept mapping. In *Proceedings of the 8th International Conference of the Learning Sciences 2008 (ICLS 2008)* (pp. 91–98). ISLS.

Müller-Tomfelde, C., & Fjeld, M. (2012). Tabletops: Interactive Horizontal Displays for Ubiquitous Computing. *Computer* (February), 78–81.

Nielsen, J. (1993). Usability Heuristics. In *Usability Engineering*. San Francisco: Morgan Kaufmann.

Novak, J. (1995). Concept mapping to facilitate teaching and learning. *Prospects, 25*(1), 79–86.

Novak, J., & Cañas, A. (2008). The Theory Underlying Concept Maps and How to Construct and Use Them *Technical Report IHMC CmapTools 2006–01*. Available online: http://cmap.ihmc.us/Publications/ResearchPapers/TheoryCmaps/TheoryUnderlyingConceptMaps.htm.

Olson, J. S., Teasley, S., Covi, L., & Olson, G. (2002). The (currently) unique advantages of collocated work. In *Distributed work: New research on working across distance using technology* (pp. 113–136). Cambridge, MA: MIT Press.

Oppl, S., & Stary, C. (2011). Effects of a Tabletop Interface on the Co-construction of Concept Maps. In *Proceedings of the Human-Computer Interaction 2011 (INTERACT 2011)* (pp. 443–460). Berlin: Springer.

Perera, D., Kay, J., Koprinska, I., Yacef, K., & Zaiane, O. (2009). Clustering and sequential pattern mining of online collaborative learning data. *IEEE Transactions on Knowledge and Data Engineering, 21*(6), 759–772.

Piper, A. M., & Hollan, J. D. (2009). Tabletop displays for small group study: affordances of paper and digital materials. In *Proceedings of the 27th International Conference on Human Factors in Computing Systems (CHI 2009)* (pp. 1227–1236). New York: ACM.

Race, P. (2001). *A briefing on self, peer and group assessment*. (Assessment, Vol. 9). York Learning and Teaching Support Network Generic Centre.

Rick, J., Harris, A., Marshall, P., Fleck, R., Yuill, N., & Rogers, Y. (2009). Children designing together on a multi-touch tabletop: An analysis of spatial orientation and user interactions. In *Proceedings of the 8th International Conference on Interaction Design and Children 2009 (IDC 2009)* (pp. 106–114). New York: ACM.

Rick, J., Marshall, P., and Yuill, N. (2011). Beyond one-size-fits-all: How interactive tabletops support collaborative learning. In *Proceedings of the 10th International Conference on Interaction Design and Children (IDC 2010)* (pp. 109–117). 1999043: ACM.

Rogers, Y., & Lindley, S. (2004). Collaborating around vertical and horizontal large interactive displays: Which way is best? *Interacting with Computers, 16*(6), 1133–1152.

Roman, F., Mastrogiacomo, S., Mlotkowski, D., Kaplan, F., & Dillenbourg, P. (2012). Can a table regulate participation in top level managers' meetings? In *Proceedings of the 17th International Conference on Supporting Group Work (GROUP 2012)* (pp. 1–10). New York: ACM.

Roschelle, J., & Teasley, S. D. (1995). The Construction of Shared Knowledge in Collaborative Problem Solving. In *Computer Supported Collaborative Learning.* (pp. 69–97). Berlin: Springer.

Scardamalia, M., & Bereiter, C. (1991). Higher levels of agency for children in knowledge building: A challenge for the design of new knowledge media. *Journal of the Learning Sciences, 1*(1), 37–68.

Scheuer, O., Loll, F., Pinkwart, N., & McLaren, B. (2010). Computer-supported argumentation: A review of the state of the art. *International Journal of Computer-Supported Collaborative Learning, 5*(1), 43–102.

Siemens, G., & Baker, R. S. J. d. (2012). Learning analytics and educational data mining: Towards communication and collaboration. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK 2012)* (pp. 252–254). New York: ACM.

Slavin, R. E. (1983). When does cooperative learning increase student achievement? *Psychological Bulletin, 94*(3), 429.

Soller, A., Wiebe, J., & Lesgold, A. (2002). A machine learning approach to assessing knowledge sharing during collaborative learning activities. In *Proceedings of the International Conference on Conference on Computer Support for Collaborative Learning 2002 (CSCL 2002)* (pp. 128–137). ISLS.

Soller, A., Martinez, A., Jermann, P., & Muehlenbrock, M. (2005). From mirroring to guiding: A review of state of the art technology for supporting collaborative learning. *International Journal of Artificial Intelligence in Education, 15*(4), 261–290.

Stahl, G. (2006). *Group Cognition: Computer Support for Building Collaborative Knowledge*. Cambridge: MIT Press

Stahl, G. (2013). Transactive discourse in CSCL. *International Journal of Computer-Supported Collaborative Learning, 8*(2), 145–147.

Talavera, L., and Gaudioso, E. (2004). Mining Student Data to Characterize Similar Behavior Groups in Unstructured Collaboration Spaces. In *Proceedings of the Workshop on artificial intelligence in CSCL - European Conference on Artificial Intelligence 2004 (ECAI 2004)* (pp. 17–23).

Tanenbaum, K., and Antle, A. N. (2009). Using Physical Constraints to Augment Concept Mapping on a Tangible Tabletop. In *Proceedings of the International Conference on Education and Information Technology 2009 (ICEIT 2009)* (pp. 539–547). San Francisco: IAENG.

Tang, A., Pahud, M., Carpendale, S., and Buxton, B. (2010). VisTACO: Visualizing tabletop collaboration. In *Proceedings of the International Conference on Interactive Tabletops and Surfaces 2010 (ITS 2010)* (pp. 29–38). New York: ACM.

Webb, N. M. (2009). The teacher's role in promoting collaborative dialogue in the classroom. *British Journal of Educational Psychology, 79*(1), 1–28.

Yu, Z., & Nakamura, Y. (2010). Smart meeting systems: A survey of state-of-the-art and open issues. *ACM Computing Surveys, 42*(2), 1–20.

Zhang, D., Zhao, J. L., Zhou, L., & Nunamaker, J. F., Jr. (2004). Can e-learning replace classroom learning? *Communications ACM, 47*(5), 75–79.