CSCL Interaction Analysis for Assessing Knowledge Building Outcomes: Method and Tool

Yanyan Li, Jian Liao, Jing Wang, Ronghuai Huang,
Knowledge Science & Engineering Institute, School of Education Technology,
Beijing Normal University, 100875, Beijing, China
Email: liyy1114@gmail.com, leojames@126.com, wangj19@gmail.com, huangrh@bnu.edu.cn

Abstract：Interaction analysis plays an important role in computer-supported collaborative learning. This paper proposes a multidimensional analysis framework to study the interaction and makes use of the quantitative analysis method to assess the collaborative knowledge building (CKB) outcomes at individual and group levels. A tool is developed that can support interaction analysis, text analysis, social network analysis and a combination of the above to show the differences of cognitive content and constructive level in terms of collaborative knowledge building. A case study of the interaction analysis via using the tool is presented.

Introduction

Computer-supported collaborative learning (CSCL) environments have been argued to foster collaborative knowledge construction. The process of collaborative learning can also be considered as a process of Collaborative Knowledge Building (CKB) (Stahl,G., 2003). In this process, learners construct shared understanding through collaborative interaction, and they are regarded as knowledge constructors rather than knowledge receivers. Therefore, analyzing the collaborative interaction between members can facilitate finding out the nature of knowledge building mechanism, which provides foundation for designing and developing CSCL environments.

So far, interaction analysis has draw close attention from many researchers. Generally, the interaction analysis methods usually fall into three levels. The first level takes the interaction as the communication to form relationship network, which emphasizes the relationship between members (Haythornthwaite, C., 1999; Nurmela, K.et al, 1999; Maarten ,L., 2002; Albrecht T.L.& Hall,B., 1991). The second level considers the interaction as the sequence combination of different speech acts, which pays more attention to the time structure relationship of communication information or activities. Hee-Jeon(2001)defines three categories (nine sub-categories) of interaction process and uses the sequence of speech acts to briefly describe the interaction. Harrer(2000)describes the interaction as a two-level conversational network. While Avouris(2003) proposes an Object-Oriented Collaboration Analysis Framework. A finer level of granularity than the speech act is focused on the ideational content. Porayska Pomsta analyzes the content based on categories of question. Clark(2005)assesses the interaction content by coding the conceptual quality of comment in Collaborative Learning (CL). By this way researchers can find more characteristics of CL at semantic level. However, there still lack an integrated method and tool to analyze CKB in CL synthetically. Furthermore, most of the researches usually use manual coding to conduct qualitative analysis of interaction content. However, qualitative manual coding involves subjective judgement and the reliability of dialogue analysis schemes remains a contentious issue (Pilkington,R., 2001).

A Multidimensional Analysis Framework to Study Interaction for Collaborative Knowledge Building

From the pedagogical viewpoint, collaborative learning should be assessed from multi-dimensions. Henri(1991), Newman(1995) analyze the performance of CSCL from group level. Stahl(2005) points out, group cognition should be centrally concerned by computer support for CKB. So it is important to regard group knowledge building level as the dimension of interaction analysis. On the other hand, according to the definition of basic elements of CL proposed by Johnson,D.W.& Johnson,R.T, (1989), individual duty is one of important factors that influence CL. This perspective shows that it is necessary to analyze group members' individual contributions in CL. Furthermore, many researches show that the relationship between group members has a great effect in CL. As Cartwright(1968)and Festinger (1950) presented, compared with the groups with loose cohesion, the members in the groups with intense cohesion have more satisfaction and happiness, and they are more inclined to participate actively, communicate frequently and seldom absent. Johnson(1989)even consider the positive interdependence as the first representative element of collaborative learning.

Therefore, by incorporating existing interaction analysis methods, we propose a multidimensional analysis framework to study interaction in terms of collaborative knowledge building (see Figure 1). The shadow ellipse represents the interaction analysis methods, which comprises three perspectives: Speech topics (i.e. the mentioned topics involved in the discussion), speech intention (i.e. the intention of speech act), and social network (i.e. member relationship and the degree of mutual support in a discussion group or community). The multi-method research framework lays the foundation to assess knowledge building outcomes with three criteria including "Group Knowledge Building Level", "Member Contribution" and "Member Mutual Support", shown as the ellipse nodes on outer triangle in Figure 1. The "Group Knowledge Building Level" indicates the collective knowledge building level of a group, and the "Member Contribution" reflects the individual performance in the collaborative learning process, while "Member Mutual Support" indicates the relationship between members as well as their speech similarities.
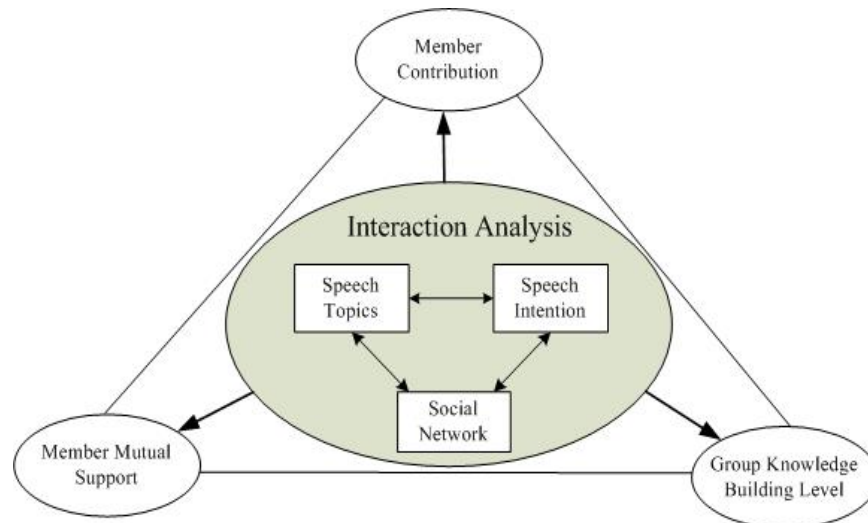

Figure 1. The Model of Integrated Interaction Analysis for CKB.

Computational Methods to Assess the Knowledge Building Outcomes
Group Knowledge Building Performance

Scardamalia&Bereiter(1994) propose there are three characteristics of the knowledge building community: "discussion related to the question promotes deeper understanding", "non-intensive and opening discussion" and "effective interaction". Fisher(1993)、Mercer(1995)、Coelho(1994)consider effective interaction as "exploratory talk", whose characteristics is that participants communicate in a critical but constructive way. To summarize, "relevance to topic", "positive negotiation" and "common participation" are three important characteristics of knowledge building level of a group. So, we adopt "Group Topic Relevance", "Group Interactive Intention Level" and "Group Equilibrium" to evaluate group knowledge building level. Group Topic Relevance indicates the relevance of whole group's speeches to the discussion topic. Group interactive-intention level reflects the degree of positive argument or negotiation that are regarded as have higher interactive level to resolve cognitive conflict in a group. Group Equilibrium represent the consistency of member participation which can reveal whether every member participate in the group interaction positively. Based on the coding schema developed by Veldhuis-Diermanse (2002), with combination of the interaction analysis model (Gunawardena,L.&Anderson, 1997) and the model of collaborative knowledge building (Stahl,G., 2003), we bring forward a coding schema focusing on the learning processes. The coding schema includes five categories "sharing", "argument", "negotiation", "meta-cognitive", and "social greeting", in which there are nineteen speech acts in total. Taken the categories as the assessment criteria, a synthetic method based on Analytic Hierarchy Process (AHP) theory is applied to make quantitative analysis and evaluation of the individual contribution and group performance.

Definition 1: Group Interactive Intention Level $\quad GI = W_{max} \dfrac{\sum_{k=1}^{n} W_k M_k}{M}$

Where n is the number of the code of speech intention, W_k represents the weight assigned to each speech intention based on Analytic Hierarchy Process (AHP) theory, W_{max} equals to the maximum of W_k. M_k is the number of speeches of kth intention. M is the total number of speeches.

Definition 2: Group Topic Relevance $\quad GR = \dfrac{GT}{T}$

Where T represents the total number of words in the domain vocabulary, GT represents how many words appeared in the groups' discourse are included in the domain vocabulary.

Definition 3: Group Equilibrium $\quad GE = 1 - \dfrac{D}{D_{max}} = 1 - \dfrac{D \cdot S \sqrt{S-1}}{N(S-1)}$

Where D is the standard deviation of the speech numbers in a group, D_{max} is the max value of D. S is the number of members, N is the number of speeches.

Definition 4: Group Knowledge Building Level $\quad GKBL = \alpha_1 GR + \alpha_2 \cdot GI + \alpha_3 \cdot GE$

Where $\alpha_1, \alpha_2, \alpha_3$ are the adjustment factors used to scale the importance of GR, GI and GE, respectively. It can be proved that the values of each factor are all between [0, 1].

Member Contributions to Collaborative Knowledge Building

Newman(1995) and Liu(2005) both consider the novelty of members' speeches and the extension of the topic to be discussed as the important criteria of evaluating the quality of interactive texts. Additionally, Albrecht&Hall(1991), Baldwin, Bedell & Johnson (1997), Haythornthwaite (1999) all think the centralization of members in a social network will influence the member's performance in a group. So we adopt "Relevance", "Novelty", "Extension", "Interactive Intention Level" and "Member Centralization" to assess member contributions.

Definition 5: Relevance $\quad R_i = \dfrac{M_i}{M}$

Where M_i represents the number of topic words which are talked in the speeches of the ith member. M represents the total number of words in the topic vocabulary.

Definition 6: Novelty $\quad V_i = V_{max} \dfrac{P_i}{N}$

Where P_i represents the number of keywords mentioned for the first time by group member i. N represents the total number of keywords.

Definition 7: Extension $\quad E_i = E_{max} \dfrac{N_i}{N}$

Where N_i represents the number of keywords in each member's speeches. N represents the total number of keywords in the whole discussion speeches.

Definition 8: Interactive Intention Level $\quad I_i = W_{max} \sum_{k=1}^{n} \left(\dfrac{M_{ik}}{M_i} \times W_k \right)$

Where n is the number of the code of speech intention. W_k is the weight assigned to the kth speech act by using AHP approach. W_{max} equals to the maximum of W_k. M_{ik} indicates the number of ith member's speeches that are coded as kth speech act, M_i indicates the total number of speeches of ith member.

Definition 9: Member Centralization $\quad C_i = \dfrac{ID_i + OD_i}{2S - 2}$

Where S is the number of student. ID_i indicates the number of ith member's in-degree of social network, OD_i indicates the number of ith member's out-degree of social network.

Definition 10: Member's Contribution $\quad MC_i = \beta_1 R_i + \beta_2 V_i + \beta_3 E_i + \beta_4 I_i + \beta_5 C_i$

Where β_i (i=1, 2, 3, 4, 5) is the adjustment factor that represents the importance degree of each factor.

Group Member Mutual Support

Social Network Analysis (SNA) is usually used to find the relationship between members by counting the number of reply-messages between members, which doesn't consider the content of the speeches. However, we believe that the more similar of two members' speeches, the mutual support will be greater. As a complement, we take into account the content and intention of speech to augment the SNA. The algorithm of similarity is the same as the vector cosine method which is frequently used in calculating the document similarity in text mining technology.

<u>Definition 11: Member's Speech Content Support</u>

$$CS_{ij} = \frac{F_i \bullet F_j}{|F_i| \times |F_j|} = \frac{\sum\limits_{k=1}^{N} F_{ik} \times F_{jk}}{\sqrt{(\sum\limits_{k=1}^{N} F_{ik}^2)(\sum\limits_{k=1}^{N} F_{jk}^2)}}$$

Where F_i represents the vector of word frequency in member i's speeches in the vector space model (VSM). F_j represents the vector of word frequency of keywords in member j's speeches. F_{ik} represents the word frequency of the kth keyword in the speeches of the ith user. F_{jk} represents the word frequency of the kth keyword in the speeches of the jth user. N represents the total number of keywords. Therefore, we can obtain the matrix of the degree of member's support CS, which represents the degree of mutual support among group members.

<u>Definition 12: Member's Speech Intention Support</u> $IS_{ij} = W_{max} \dfrac{\sum\limits_{k=1}^{n} W_k M_{ijk}}{M_{ij}}$

Where n is the number of the code of speech intention. W_k is the weight assigned to the kth speech act by using AHP approach, W_{max} equals to the maximum of W_k. M_{ijk} indicates the number of ith member's speeches which reply the jth member and are coded as kth speech intention. M_{ij} indicates the total number of speeches of ith member who reply to the jth member. Above factors can be proved that their values are between [0, 1].

Implementing a Tool to Support Interaction Analysis

We have developed a tool VINCA (Visual Intelligent Content Analyzer) with C# language to support interaction analysis. It is implemented by using C/S architecture and can be installed stand-alone or support the online downloading of the forum text from CSCL platform (currently support WebCL platform http://www.webcl.netc.cn) to conduct analysis. The tool provides a plug-in interface allowing for flexible addition of more modules. VINCA can support coding analysis, text analysis, social network analysis and a combination of the above to assess the CKB outcomes for showing the differences of cognitive content and constructive level in terms of collaborative knowledge building. It is worth to note that VINCA distinguishes from other similar tools with three features: 1) Learnable semi-automatic coding support; 2) Text Analysis for traditional and simplified Chinese; 3) Compute content similarity of user speech. Herein we give several snapshots of the VINCA interface (see Figure 2, 3, 4). In brief, VINCA mainly has the following functions.

- Flexible data source selecting. VINCA can automatically parse the discourse data in the HTML format and then store in the database. Currently it supports the data format of Knowledge Forum (http://www.knowledgeforum.com/) and WebCL (http://www.webcl.net.cn) platform. Users can select the specific data sources according to his specified filtering variables, such as speakers, keywords, time, coding, or the combination of the above variables.
- Semi-automatic coding aids. Besides supporting the users to manually code, VINCA can learn the coding hint by using machine learning method. In this way, VINCA can automatically discover the code hint, highlight it and associate it with recommended codes.
- Keywords extraction & frequency counting. VINCA fulfills the task of extracting meaningful keywords and counting their frequency. As complement, uses can specify domain lexicon or exclusive keywords list to focus on some specific keywords or exclude some useless keywords.
- Concordance (keywords in context). Users can click the keywords to view the context in which they appear.
- Group & individual performance analysis. By means of the above methods, VINCA computes the assessment

indicators for evaluating the group and members' contribution and performance.

- Data export for SNA. VINCA provides several output data sets for augmented social network analysis, such as export relation matrix, export coding result, export coding matrix, content similarity matrix, etc.
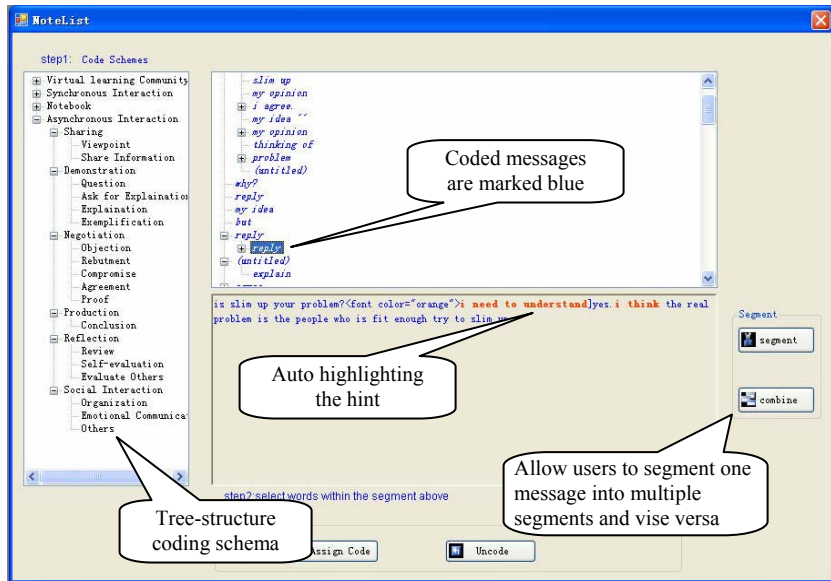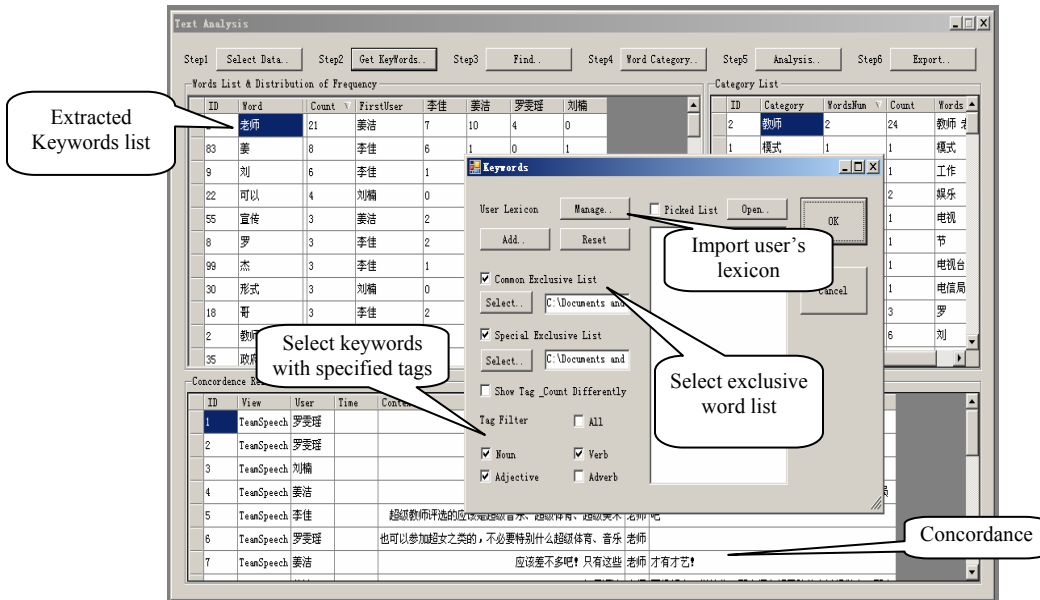

Figure 2. Semi-automatic Coding

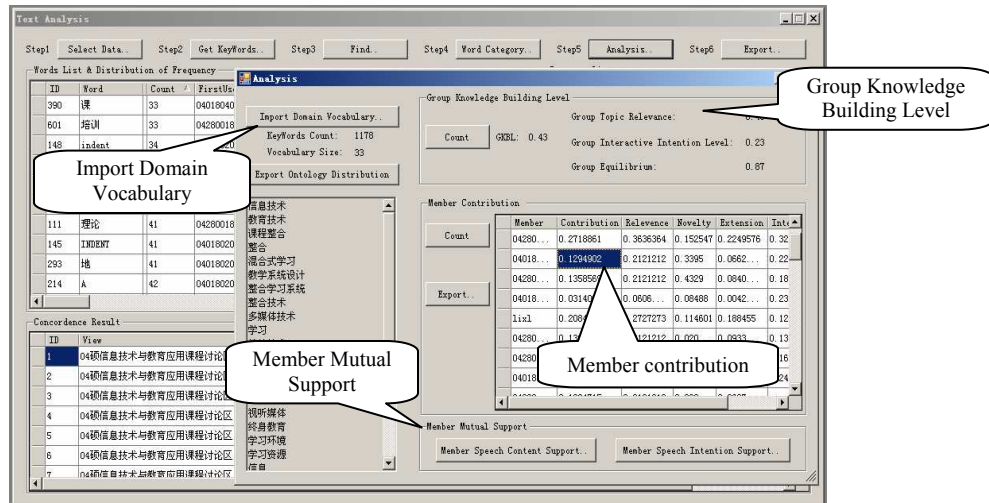Figure 3. The interface to view the keyword extraction and concordance.

Figure 4. The interface displaying the computerized group and individual performance.

A Case Study of Interaction Analysis

We have developed an e-learning platform WebCL (available at http://www.webcl.net.cn/) that has been used in more than twenty universities and high schools, and the total number of registered users exceeds 10000. VINCA can be installed stand-alone and support the online downloading of the forum text from WebCL to conduct analysis. We chose two sets of CSCL discourse data of two classes of graduate students enrolled in the same course "Information Technology and Educational Application". The two classes are respectively taken as group A (number of total students is 47) and group B (number of total students is 87). With the assistance of VINCA, we followed a four-step process to conduct the comparison analysis in terms of collaborative knowledge building, including group knowledge building level, member contribution and member mutual support. The process comprises: 1) Import the data in HTML format into VINCA. 2) With the semi-auto coding support of VINCA, coded all the discussion messages of the two groups. 3) VINCA was used to generate the frequencies of meaningful keywords found in the discussion discourse, and extraction of text in close proximity to selected keywords using concordance technique. 4) Use VINCA to export the data for SNA.

Table 1: Code scheme and weight.

Code	Weight	Sub-code	Weight	Code	Weight	Sub-code	Weight
Social Interaction	0.040	Organization(OR)	0.017	Negotiation	0.544	Objection(OB)	0.030
		Others(OT)	0.002			Rebutment(RB)	0.077
		Emotional Communication(EC)	0.005			Compromise(CO)	0.144
Sharing	0.109	Viewpoint(VP)	0.048			Conclusion(CL)	0.237
		Suggestion(SU)	0.048			Agreement(AG)	0.033
		Share Information(SI)	0.024			Proof(PR)	0.077
Argument	0.231	Question(QU)	0.030	Reflection	0.077	Review(RE)	0.033
		Ask for Explaination(AE)	0.012			Self-evaluation(SE)	0.007
		Explaination(EX)	0.063			Evaluate Others(EO)	0.013
		Exemplification(EF)	0.100				

Group Knowledge Building Level

The teacher constructed a domain vocabulary of the course that contains 35 words, such as "information technology", "educational technology", etc. As the above-mentioned method explained, this domain vocabulary is used to compute the relevance of members' speeches. To determine our inter-coder reliability we firstly, for each coded message, checked to see if the codes assigned by the two coders referred to the same parts of the message (i.e. the same units of meaning). Secondly, we checked to see if the two coders had assigned the same codes to each unit. Based on a 10% sample of all the messages coded by the two researchers, the value of Cohen's Kappa exceeds 0.7 for 16 categories. Afterwards, based on the AHP method, we assigned the weights to each code indicating the importance of each code in terms of cooperative knowledge building (C.I.<0.1)(see Table 1). According to above methods, all the messages of two groups (Group A: 237 messages; Group B: 577 messages) are coded. Figure 5, 6, 7 show the coding results in detail, which show that most of the Group B's messages are coded as "sharing"(48%) and the percentage of messages coded as argument and negotiation are 22% and 10%. In contrast, 29% messages of Group A are coded as "argument" and 21% messages of Group A are coded as "negotiation". This suggests the speeches of Group A reflect more cognitive conflicts that can foster the collaborative knowledge advance. Based on the statistical result, Figure 8 shows the computerized indictors of group knowledge building level.
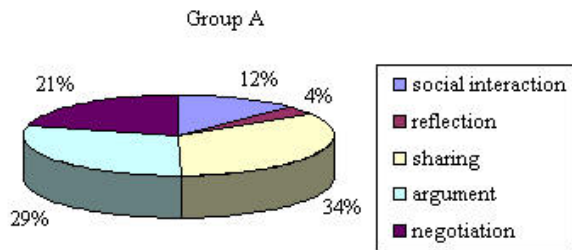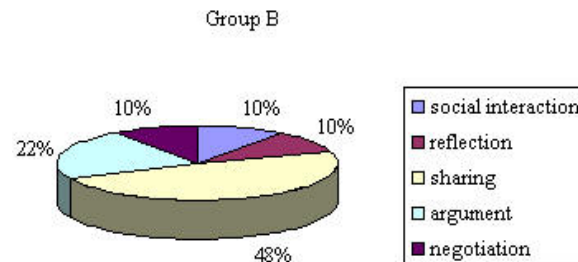

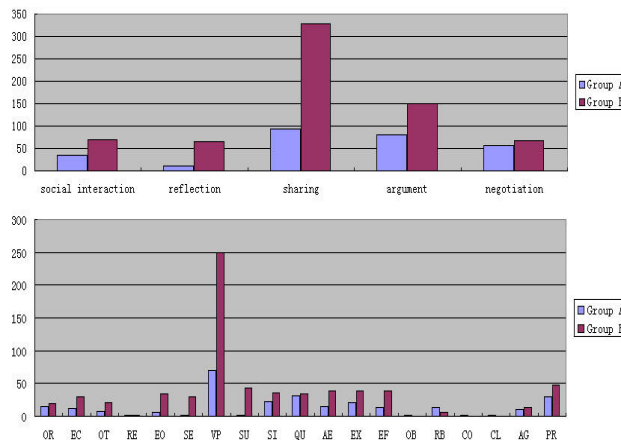Figure 5. Coding result of Group A.   Figure 6. Coding result of Group B.

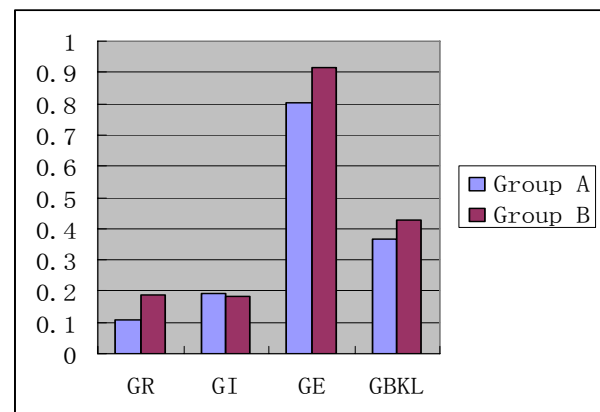Figure 7. Coding result comparison of group A and group B.   Figure 8. Group knowledge building

Member Contribution

Based on the above methods, we compute the member contribution in terms of five dimensions (Relevance, Novelty, Extension, Centric, Interactive intention). Figure 9 gives an illustrative sample of two members' contribution in the same class. From the figure, we can see that the extension level of two members is approximate, but member one (Student Number: 50280280203) performs better than member two (Student Number: 50280280153) in terms of relevance, novelty, centralization and interactive intention. This indicates the total contribution of member one is higher than member two.
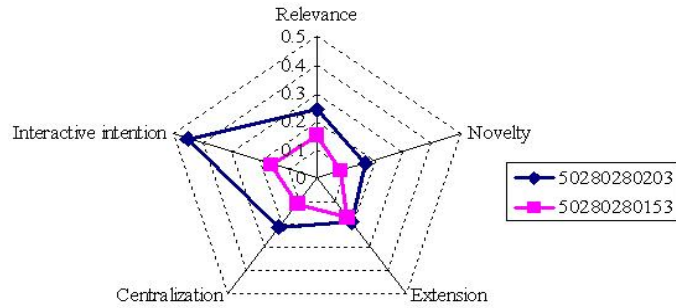
Figure 9. Illustrative sample of member contribution.

Member Mutual Support

By analyzing the reply-to relationship of messages and coding results, we drew the social network and interactive intention network of twenty members selected at random, as shown in the figure 10 and figure 11, respectively. Figure 10 illustrates the usual reply-to relationship between members. Figure 11 is an interaction intention network figure where the edge means the members' interaction intention. The wider the edge is, the higher interaction intention of the member is. For example, we discovered that the member (SN: 50280280203) not only plays a centric role, but his level of interaction intention is higher. In contrast, the level of interaction intention of member (SN: 50280280273) is lower. It suggests that this member provides more information for sharing rather than argue or negotiate with other members.
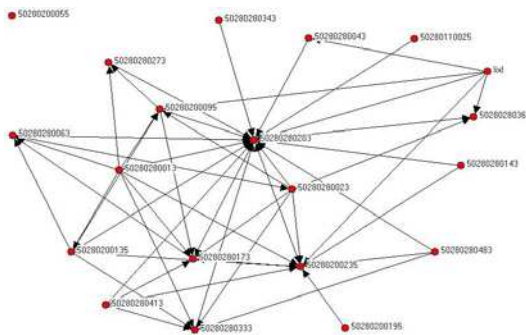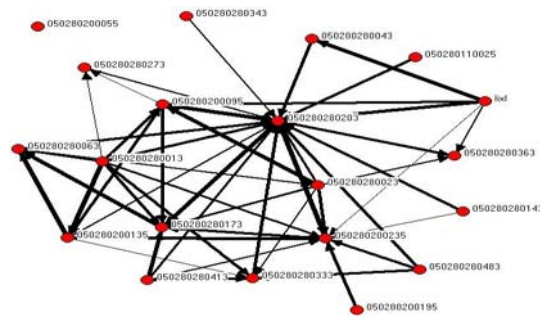

Figure 10. Social network

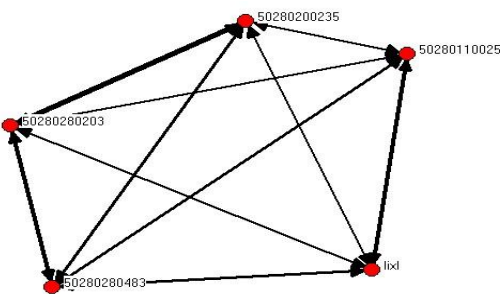Figure 11. Interactive intention network

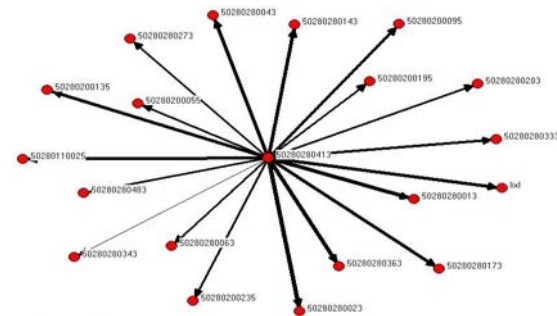

Figure 12. Grid-mode Social Network

Figure 13. Asterisk-mode social network

Moreover, the members' speech similarity matrix was exported with VINCA and we drew two-mode figures to intuitively show the members' mutual support in terms of content similarity. In the figure, the edge means the degree of speech similarity of two members. The wider the edge is, the higher similarity of two members' speeches is. Figure 12 is the grid-mode social network that gives an illustrative example of five members' mutual support. As the figure shows, the edges pointing to the member (SN: 50280280203) are wider than that of other members. It suggests that his speech drew extensive attention. Likewise, the member (SN: lixl) is another central member in the group. However, the content similarity of the two members' speeches is relatively low. From this, we can see that the different speeches presented by the two members both draw much attention from others. Figure 13 is

the asterisk-mode social network that shows the content support between a member (SN: 50280280413) and other 19 members. From the figure, we can see that the speech content similarity between him and other members is high except one member (SN: 50280280343).

Conclusion

Qualitative analysis method is widely adopted to analyze collaborative interaction. By contrast, this paper explores the quantitative method to analyze the collaborative interaction, attempting to calculate and summarize the interaction characteristics for assessing the collaborative knowledge building outcomes. We have developed a multi-method research framework to study collaborative learning processes by making use of social network analysis (SNA), content analysis (CA) and text analysis technology to assess group knowledge building level, member contribution and member mutual support. We have developed a tool to assist the interaction analysis, and conducted a case study with the tool on two sets of CSCL discourse data from two comparable classes. The results show the differences of cognitive content and constructive level between two classes, and provide suggestive findings for assessing the knowledge building outcomes at individual and group level.

Further investigations are needed to analyze the various roles the participants play in the collaborative learning, and to examine how individual and collective knowledge advances intertwined. Meanwhile, apply the tool in more practical education settings and to improve it according to the feedback from researchers and teachers.

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