Effect of Presenting Co-occurrence Networks that Reflect the Activeness of Face-to-Face Discussions

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Abstract. This paper proposes a system that presents outlines of discussions in other groups in the same classroom as co-occurrence networks that reflect the activeness of discussions. The proposed system focuses on discussions conducted by two people during a lecture. The activeness of the discussions is analyzed using nonlinguistic acoustic information, which is calculated based on participants utterances collected by wearable devices. The co-occurrence networks are drawn with emphasizing the active parts of discussions by each group. We conducted an experiment to verify the effect to the participants by applying the proposed system to a lecture, and the effect of presenting the co-occurrence networks was examined in a subjective evaluation. The participants conducted another discussion after observing the co-occurrence networks of the previous discussion, and the second discussion was scored by the lecturer. As a result, the co-occurrence networks reflecting discussion activeness were not evaluated higher than those that did not reflect discussion activeness. This suggests that the variety of topics in the co-occurrence networks may stimulate discussion participants more effectively.

Keywords: Group discussion · Co-occurrence network · Nonlinguistic acoustic information · Word embedding

1 Introduction

Tackling complex problems are difficult, with the limits in individuals' perspectives, experiences and knowledge. Creative activity grows out of the relationship between an individual and other human beings. Because complex problems require more knowledge than any single person possesses, it is essential that all involved learners participate, communicate, collaborate from each other [1].

Active learning, which is worked on a problem and actively involved its learning process, has been introduced in the education field. One active learning approach introduces a discussion style in which divide small groups are formed during a lecture. In discussions, it is important to hear and understand the opinions

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of others. However, in such small-group discussions, the opinions of participants maybe similar if the learners are in the same field of study. In such cases, the range of discussion can be limited; thus, it may be difficult to include unexpected opinions. To solve this problem, it is useful to incorporate different opinions and ideas from outside the group into the discussion.

To incorporate different ideas from outside the group, several group discussion techniques have been proposed such as jigsaw method [2], sharing comments on worksheets, and providing a list of keywords. However, these methods have problems in supporting ideas and activating discussions. For example, when sharing opinions among groups using the jigsaw [2], the degree of success depends on the level of understanding of the target learners. If the learner cannot summarize the discussion effectively, sharing opinions with other learners cannot be achieved. And stable membership groups experienced higher levels of comfort and perceived friendliness than did groups that changed membership [3]. In discussion, it is possible that changed membership prevent from discussion activeness. In addition, when using comments on worksheets, the learner requires significant time to understand the details of the discussion because a lot of information may be shared. With a list of keywords, it is possible to grasp an outline of the discussion; however, it may be difficult to understand the entire discussion because the general context is omitted. Thus, in this study, to obtain general understanding of the context of a discussion, we propose a method to present words that evoke the subject of the discussion.

The proposed method comprises three main phases, i.e., Discussion Phase 1, Support Phase, and Discussion Phase 2. After Discussion Phase 1, the proposed system presents a co-occurrence network to participants. Using the proposed system, we examine how the proposed system affects Discussion Phase 2.

2 Related Work

2.1 Visualizing Discussion Outlines

Previous studies have investigated visualizing discussion content. For example, a previous study [4] visualized discussion using extruded word clouds. Here, the authors created word clouds in consideration of the number of participants involved topic words in a given period. By looking at word clouds, it is possible to identify when the discussion topic become hot or cold. In addition, by connecting the same words in adjacent word clouds, it is possible to observe the emergence of new words, the extinction of weak words, and the existence of surviving words.

Another study proposed a method to view tags related to previous topics selected by a user [5]. As a result, the supporting system helps users remember previous conversation topics and demonstrates that viewing tags is less burdensome than checking a chat log.

2.2 Recommend Next Topic Idea

Wang [6] helps with new ideas by presenting images that is highly relevant to the word of user's input. In brainstorming, the system searches ideas in the discussion based on the corpus and presents images related to the keywords contained in the ideas. The presentation of images may let users to give information that is unrelated to the theme. Therefore, it is insufficient as a presentation method for the users to understand the outlines of the discussion.

In addition, Sunayama [7] proposed a system that recommends a next topic that is related to the current topic. This system uses the hit counts of a web search engine to evaluate the relations of the current topic, and the top-five words of the number of hit counts are presented by users. The purpose of this system is keeping the conversation. Note that the presented topics are general; thus, this system is unlikely to stimulate discussions.

3 Discussion Support Based on the Condition

3.1 Presenting Co-occurrence Networks that Reflect Activeness of Discussions

In this study, to understand an outline of a complete discussion in a short period, we proposed a system that presents words that evoke the topic of the discussion using co-occurrence networks. A co-occurrence network is a network diagram of the similarity of the patterns in which words appear. However, if the co-occurrence network is simply drawn from utterances in the discussion, the discussion topics can become dispersed, and it may be difficult to quickly understand the discussion.

Thus, to encourage participants to lead to new ideas, we introduce a method to emphasize active parts of a discussion when drawing the co-occurrence network. Active parts of a discussion are likely to be an attractive topic for the group. In addition, the participants are actively involved these parts of the discussions therefore, the participants of other groups could easily sympathize with the discussion content. We consider that these parts of a discussion well represent the overall discussion. Therefore, we consider that participants can understand discussion outlines easily by emphasizing the most active parts of a discussion.

In addition, it is necessary to consider the characteristics of the other groups. Here, we focus on a group with low relevance to the original group's discussion. We expect that using the content of a group not mentioned by the original group would be stimulating for the original group.

3.2 Nonlinguistic Acoustic Features

Here, the following features are introduced to estimate the activeness of a discussion [Anonymous, 2019]: time percentage of an utterance, percentage of silence, and coefficient of speech overlap. Note that these values are calculated using only nonlinguistic acoustic information per unit time.

Time Percentage of Utterance. The time percentage of an utterance value is the utterance duration of a participant per unit time. The time percentage of utterance is calculated for each participant in a group discussion, and the value is given in the range 0% to 100%. The degree of participation of each participant in the discussion is obtained by evaluating the transition of the time percentage of an utterance.

Percentage of Silence. The percentage of silence value is the duration in which no group member spoke per unit time, and it is calculated per group (rather than for each individual). The value is given in the range 0% to 100%. The degree of stagnation of the group is obtained by evaluating the transition of the percentage of silence.

Coefficient of Speech Overlap. The coefficient of speech overlap is the sum of the total time percentage of an utterance of all participants in and the percentage of silence of the group during a discussion, and it is calculated per group (rather than for each individual). This value is given in the range 1 to the total number of participants in the group. In addition, if there is no speech overlap, the coefficient of speech overlap is 1. The degree of activeness in the group can be determined by evaluating the transition of the coefficient of speech overlap.

3.3 Wearable Device

Wearable devices are consists in reference to previous research[9]. Here, Raspberry Pi 3B+ or Raspberry Pi 4B are attached to a unidirectional USB microphone that records the participants' utterances. Figure 1 shows the wearable device. The utterance audio data of the utterances are recorded and stored as WAVE format files in the wearable devices. In addition, the nonlinguistic acoustic features are calculated by a server using the CSV files saved in the wearable devices.

In this study, we evaluated whether the discussion was active every 20 s. Using the nonlinguistic acoustic features collected in Discussion Phase 1, the threshold to assess whether the discussion was active or inactive was determined (Sect. 5.1). Then, the weight of words in the active parts of the discussion were treated as double-counted. As a result, the active parts of the discussion can be emphasized and reflected in co-occurrence networks.

3.4 Converting Utterance into Text in the Discussions

Using the audio files collected by the wearable devices, the discussion content of each participant is to text using Google Cloud Speech-to-Text. However, Cloud Speech-to-Text could not add punctuation marks at that time, and punctuation is essential to draw the co-occurrence networks. In addition, the recognized precision was reduced by informal term in the discussions. Therefore, after performing the speech recognition process, punctuation marks were added and erroneous conversions were corrected to refine the text.

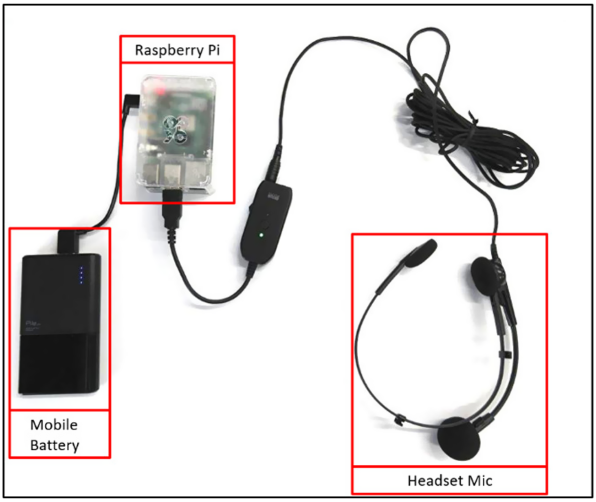

Fig. 1. Wearable device

3.5 Relevance to the Contents of the Discussion

In this study, we considered it is necessary to use the co-occurrence network of a group with low relevance to the discussion content to stimulate discussion. Using the content of another group not mentioned by the original group is expected to stimulate the original group to think about new ideas related to the target subject matter. Thus, Word2vec [9], which represents the meaning of a word using vectors, was used to compare the relevance of the discussion content. Here, the similarity of the content of the discussions was calculated between groups. In a previous study, word embedding was used to support conversation. Nishihara [10] proposed a topic switching system for unfamiliar couples in face-to-face conversations. When couples end the conversation, this system selects a new topic and presents the new topic to the couples.

In this study, the existing trained model was used. Here, the Wikipedia data are used as learning data, and the feature vector for each word is 300 dimensions. In addition, the meanings of words are considered; thus, this method is more human-friendly than word coincidence among discussions. To select the new topic, the information of both hobbies collected are vectorized using Word2vec, and then words that are highly related to those words are presented to the user as next topic words.

The original goal of Word2vec is to compare the similarities of words. However, in this study, the vector averages of words are compared. This method hardly generates the difference as the number of words increases. Thus, similarity increases even for unrelated sentences.

Here, we extract topic words in the discussion, and we employed TF-IDF to search these words, where the weight of a term that occurs in a document is proportional to the term frequency. The specificity of the term can be quantified as an inverse function of the number of documents in which it occurs. With these ideas, TF-IDF can be used to measure the importance of words in documents. TF-IDF is expressed by Eqs. (1), (2), and (3). Here, $n_{t,d}$ is the number of times words t appear in group d, n_d is the number of appearance of all words in group d, N is the total number of groups, and df(t) is the number of groups in which word t appears.

$$tfidf(t,d) = tf(t,d) \cdot idf(t,N) \tag{1}$$

$$tf(t,d) = \frac{n_{t,d}}{n_d} \tag{2}$$

$$idf(t,N) = \log \frac{N}{df(t)} + 1 \tag{3}$$

As a result, the top-five words are selected from the TF-IDF value. If the words have same values, they are ranked according to the number of links in the co-occurrence network for that word.

The discussion data converted to text were subjected to morpheme analysis using Mecab [11] to extract nouns. Then, the top-five nouns were selected as topic words using the TF-IDF method. Each topic word was then vectorized using Word2vec, and it was averaged. Thus, the feature vector in the group discussion can be calculated. When selecting topic words, we excluded words containing numbers and those that did not appear in the co-occurrence networks of the group. We estimated the discussion relevance by comparing the feature vectors in the discussions of each group using cosine similarity (Eq. (4)). Here, the feature vector of discussion content a is denoted $\overrightarrow{a}$, and the feature vector of discussion contents b is denoted $\overrightarrow{b}$. This similarity takes minimum 0 and maximum values of 0 and 1, respectively, where a higher values indicates higher similarity.

$$cos(a,b) = \frac{\overrightarrow{a} \cdot \overrightarrow{b}}{|\overrightarrow{a}||\overrightarrow{b}|} \tag{4}$$

3.6 Creating the Co-occurrence Networks

The KHcoder text analysis was used to draw the co-occurrence networks from the discussion text. Calculating the co-occurrence relationship uses the Jaccard index. The calculation of the co-occurrence relation between words X and Y is expressed in Eq. (5). Here, that X and Y are the number of appearances of each word, and we selected "sentence" as the unit of aggregation.

$$Jaccord(X,Y) = \frac{|X \cap Y|}{|X \cup Y|} \tag{5}$$

Note that we excluded several parts of speech, e.g., interjections and adverbs that have no characteristic meaning. In addition, we used the TermExtract Perl module for automatic keyword extraction to detect and extract compound words.

3.7 Flow of Co-occurrence Network Presentation

As mentioned previously, we consider that a discussion comprises Discussion Phase 1, Support Phase, and Discussion Phase 2. The content of Discussion Phase 1 for all groups is converted to text (Sect. 3.4). Then, the activeness of the discussion is reflected in the text (Sect. 3.3). Next, the co-occurrence networks are drawn (Sect. 3.6) using these data. Then relevance is then is determined using the method described in Sect. 3.5. From the results, we select the group with the lowest relevance to the original group. Then, the co-occurrence network of the selected group is presented in the Support Phase. Figure 2 shows the flow of co-occurrence network presentation.

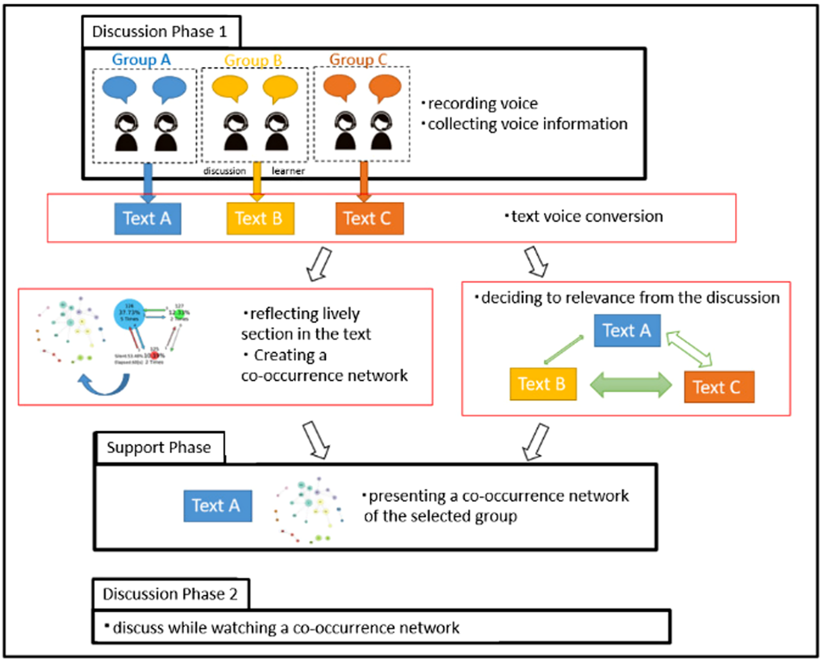

Fig. 2. Flow of co-occurrence network presentation

4 Experiment

We conducted an experiment to validate how the proposed system affects Discussion Phase 2.

4.1 Experimental Procedure

This experiment was conducted during a science lecture held at a university's interdisciplinary faculty. The participants included 36 undergraduates who gave informed consent. Note that the control condition was based on the proposed system without using discussion activeness. Each group comprised two participants. In total, there were seven groups for the experimental condition and 11 groups for the control condition. This 90-min lecture was held during the second semester of 2019. Discussion Phase 1 was held during the eleventh lecture, and Discussion Phase 2 was held in the thirteenth lecture. Note that all participants attended the lecture on both days. In addition, the group compositions were fixed throughout the experimental procedure.

In the 11th lecture on the first day, only the Discussion Phase 1 was conducted. Prior to starting the experiment, an outline of the experiment was provided, and the wearable devices were explained. In addition, teaching assistances provided a demonstration. Then, Discussion Phase 1 was conducted for 10 min. The participants engaged discussion while wearing headset microphones. Based on the content of Discussion Phase 1, the system drew and selected co-occurrence networks to be presented to each group using the procedure described in Sect. 3.7.

In the 13th lecture on the second day, the Support Phase and Discussion Phase 2 were conducted. Here, the participants formed the same groups used in Discussion Phase 1 before lecture began. Before starting the Support Phase, the experiment was explained again. In addition, the co-occurrence network was introduced. In the Support Phase, a worksheet with the selected co-occurrence network was distributed to each participant. Here, one optimal co-occurrence network for the experimental or control conditions was selected for each group. Each participant was given three minutes think about the worksheet. During this time, the participants were asked circle the parts of the co-occurrence networks that they expected to be treated as topics in Discussion Phase 2. Then, five minutes were given for Discussion Phase 2. After Discussion Phase 2, the participants were asked to answer a questionnaire to evaluate the proposed system and describe Discussion Phase 2. Table 1 shows the themes of the discussions in Discussion Phases 1 and 2, and Table 2 describes the experimental procedure.

Table 1. Discussion theme

Phase	Discussion theme
Discussion Phase 1	Explain the achievements of this faculty that you belong to
	The targets are people who do not know this faculty
	Example
	What did you grow most after entering university?
	How have you overcome your weakness?
	How would you like to use your university experience in the future?
Discussion Phase 2	What you noticed and discovered while checking the co-occurrence
	Network of the other group

Table 2. Experimental procedure

Day	Time	Contents
Day 1	5 min	Explain about experiment and demonstration
	2 min	Explain about wearable device
	10 min	Discussion Phase 1
Day 2	2 min	Explain the co-occurrence networks
	3 min	Support Phase
	5 min	Discussion Phase 2
	After discussion	Questionnaire about this system

4.2 Evaluation Item

Table 3 shows the question items of the subjective evaluation questionnaire Likert scale: "5. Strongly Agree," "4. Agree," "3. Neither Agree nor Disagree," "2. Disagree," and "1. Strongly Disagree."

Table 3. Experimental procedure

Question	Contents
Q1	You understood the contents in other group by seeing the co-occurrence network
Q2	Seeing the co-occurrence network triggered utterance
Q3	You came up with new ideas by seeing the co-occurrence network
Q4	Seeing the co-occurrence network was useful in this discussion

After Discussion Phase 2, the participants were asked to outline Discussion Phase 2 on the worksheet. In addition, the content of Discussion Phase 2 was converted to text using the method described in Sect. 3.4, and the spoken text was created. The grades of the worksheets were evaluated in three levels by the lead teacher. Here, the ratio of the high evaluation was 15%, the ratio of the middle evaluation was 70%, and the ratio of the low evaluation was 15%. The worksheets were scored according to the same criteria as the other day's lessons in other themes of the lecture. In addition, the text data were evaluated in three levels by the teachers. The ratio of the high evaluation was 30%, the ratio of the middle evaluation was 40%, and the ratio of the low evaluation was 30%. Here, the text that deepened the meaning and relationship of links in the co-occurrence network was ranked higher, and the text in which the intention of the content could not be observed in the co-occurrence network was ranked lower. The rest was standard discussion. The scoring criteria for the worksheet and spoken text are shown in Tables 4 and 5, respectively.

The participants were asked to provide a freeform response to the following: "Please state what you thought during the lecture and the reason."

Table 4. Evaluation of the worksheet

Grade	Percentage	Criteria
High	15%	Not only the facts, but also thinking deep
Medium	70%	Describes according to the set issues about the fact
Low	15%	The worksheet in which the intention of the content could not be read

Table 5. Evaluation of discussion log

Grade	Percentage	Criteria
High	30%	Spoken text that deepened the meaning and relationship of the links in the co-occurrence networks
Medium	40%	Spoken text in which based on presenting the fact about the co-occurrence networks
Low	30%	Spoken text in which the intention of the content could not be observed in the co-occurrence network

5 Result of the Experiment

5.1 Decision on Co-occurrence Networks

The threshold of discussion activeness was determined from the results of the Discussion Phase 1. Here, the nonlinguistic acoustic features of Discussion Phase 1 were analyzed. Table 6 shows the details of the nonlinguistic acoustic features for Discussion Phase 1. As mentioned in Sect. 3.3, discussion activeness was evaluated every 20 s. In reference to a previous study [8], the threshold of discussion activeness was defined as follows.

Table 6. Analysis of Discussion Phase 1

	Time percentage of utterance	Percentage of silence	Coefficient of speech overlap
Average	37.01%	31.41%	1.054
SD	6.44%	10.66%	0.039

(1) Time Percentage of Utterance for 20 s is greater than 43.45%
(2) Percentage of Silent Time for 20 s is less than 31.41%
(3) Coefficient of Speech Overlap for 20 s is the top 33% of each group

The values of the upper 33% of the coefficient of speech overlap in each group were defined based on the hypothesis that the characteristics of responses from each participant differ in existence of utterance. The threshold of the time percentage of utterance is the sum of the average and standard deviation of all groups, and the threshold of the percentage of silence is the average of all groups. Based on this threshold, we determined whether a certain part of the discussion was active for each part. Here, the weight of the words in active parts of the discussion is treated as double-counted when the system drew the co-occurrence networks.

From the results of Discussion Phase 1, co-occurrence networks with the least relevance were selected for each group (Sect. 3.6). If there were only a few active parts in the discussion, similar co-occurrence networks were drawn. Therefore, the groups in which active parts of discussions were less than 120 s were excluded as co-occurrence network candidates. In addition, to avoid presenting the same co-occurrence network to multiple groups repeatedly, no more than five groups were presented the same co-occurrence network.

5.2 Results of Questionnaire

Table 7 shows the questionnaire results. There were 14 participants in the experimental condition and 21 participants in the control condition. Note that one participant was excluded. As shown in Table 7, the average value of Q2 ("Seeing the co-occurrence network triggered the utterance") is less than those for the other three questions. Here, for each question, the Mann-Whitney U-test was performed on the hypothesis, i.e., the scores in the experimental condition are greater higher than those of the control condition. However, no significant difference was observed for either case.

Table 7. Result of the questionnaire

		Q1	Q2	Q3	Q4
Experimental	Average	3.79	3.36	3.57	3.64
Condition (N = 14)	SD	1.01	1.17	0.82	0.90
Control	Average	3.81	3.62	3.81	4.05
Condition (N = 21)	SD	1.01	0.84	0.79	0.79

As a result, the average evaluation scores were greater than three in all cases. Therefore, we consider that the proposed system with co-occurrence networks has a certain degree of acceptance for the participants.

5.3 Result of the Contents of the Discussion

Based on the criteria listed in Tables 4 and 5, "high: excellent discussion" was considered three points, "medium: standard discussion" was considered two points, and "low: insufficient discussion" was considered one point. Here, 14 participants were included in the experimental condition and 22 participants were included in the control condition. Table 8 shows the average and standard deviation of the results of the spoken text as evaluated by the teacher, and Table 9 shows the average and standard deviation of the results of the worksheets as evaluated by the teacher. Here, the Mann-Whitney U-test was performed on the hypothesis that the scores in the experimental condition are greater than those in the control condition. However, no significant difference was observed in either case. In addition, the spoken text and worksheet in the control condition were evaluated higher than those in the experimental condition.

Table 8. Result of worksheet evaluated by teacher

	Average	SD	Number and percentage of high evaluation	Number and percentage of middle evaluation	Number and percentage of low evaluation
Experimental condition (N = 14)	2.00	0.54	2 (14.3%)	10 (71.4%)	2 (14.3%)
Control condition (N = 22)	2.18	0.83	10 (45.5%)	6 (27.3%)	6 (27.3%)

Table 9. Result of spoken text evaluated by teacher

	Average	SD	Number and percentage of high evaluation	Number and percentage of middle evaluation	Number and percentage of low evaluation
Experimental condition (N = 14)	2.00	0.54	2 (14.3%)	10 (71.4%)	2 (14.3%)
Control condition (N = 22)	2.18	0.65	7 (31.8%)	12 (54.5%)	3 (13.6%)

5.4 Evaluation of the Impression in the Lecture

Several negative opinions were observed in the written comments, e.g., "I did not understand the co-occurrence network for the first time," "There was little explanation of the co-occurrence networks," and "I do not know how the co-occurrence network was drawn." We consider that these comments were given because the introduction of the co-occurrence networks was insufficient to realize effective understanding. It appears that it we must provide additional information so that the participants can become more familiar with co-occurrence networks, e.g., by providing demonstrations using co-occurrence networks. In addition, one participant stated, "I want to look back on our group's co-occurrence network." Thus, we consider that it may be helpful for participants to compare the co-occurrence networks of their own group with those of other groups. It was also suggested that the presentation to the participants who never see the co-occurrence networks is difficult to understand.

In contrast, positive opinions were provided in the written comments, e.g., "That's new for me" and "I get my idea from discussions of the other group." In addition, one participant stated, "it was inconvenient, but I thought deeply by complementing." In other words, we consider that observing the co-occurrence network facilitates further thought.

6 Discussion

In the experiment, the scores in the controled condition is higher than those in the experimental condition in the questionnaire, the worksheet and the spoken text. But there is no significant difference of the results. One of the reason for this is the fact that the range of the discussions appeared in the co-occurrence networks of the experimental condition are narrower than those of the controlled condition. This result suggests that the variety of the topics in the co-occurrence networks may stimulate utterance and idea generation of the participants in the discussions more effectively.

Another reason is assumed to be the effect of task setting. In the experiment, we set the theme that"Explain the achievements of this faculty that you belong to. The targets are people who do not know this faculty". However, this theme causes that the range of the discussions varies depending on the number of years of the grade. In addition, the examples of the question items that were expected to be created by the participants were displayed in the classroom as shown in Table 1. As a result, since the participants were affected by the examples, most of the topics of the discussions were classified into the 3 topics of the examples. The co-occurrence networks are drawn based on the co-occurrence of words. Therefore, if the topics is broke up, the co-occurrence networks will have fewer links and will be more easily broke up. In addition, there are many participants who told about their own life experiences. Therefore, the co-occurrence networks may have become difficult to be understood by the other groups.

7 Conclusion for the Future

In this paper, we have proposed a system that presents the outlines of discussions of different groups as co-occurrence networks to reflect the activeness of a discussion. In future, we plan to investigate the detailed relationships among various factors, the presentation of co-occurrence networks and adaptation of low relevance in the discussion. In addition, we plan to examine overlap between the parts of which discussions are active and the parts of which discussions are highly evaluated.

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