Discussion-skill Analytics with Acoustic, Linguistic and Psychophysiological Data

Katashi Nagao[1], Kosuke Okamoto[1], Shimeng Peng[1] and Shigeki Ohira[2]
[1]*Graduate School of Informatics, Nagoya University, Nagoya, Japan*
[2]*Information Technology Center, Nagoya University, Nagoya, Japan*

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Abstract: In this paper, we propose a system for improving the discussion skills of participants in a meeting by automatically evaluating statements in the meeting and effectively feeding back the results of the evaluation to them. To evaluate the skills automatically, the system uses both acoustic features and linguistic features of statements. It evaluates the way a person speaks, such as their "voice size," on the basis of the acoustic features, and it also evaluates the contents of a statement, such as the "consistency of context," on the basis of linguistic features. These features can be obtained from meeting minutes. Since it is difficult to evaluate the semantic contents of statements such as the "consistency of context," we build a machine learning model that uses the features of minutes such as speaker attributes and the relationship of statements. In addition, we argue that participants' heart rate (HR) data can be used to effectively evaluate their cognitive performance, specifically the performance in a discussion that consists of several Q&A segments (question-and-answer pairs). We collect HR data during a discussion in real time and generate machine-learning models for evaluation. We confirmed that the proposed method is effective for evaluating the discussion skills of meeting participants.

1 INTRODUCTION

One of the most familiar types of intellectual and creative activities is discussion at meetings. There is great significance in analyzing discussion in a scientific way and evaluating the participants' discussion skills.

Discussion skills are complex abilities, and it is difficult at present to be clearly defined as "the ability to do …" Therefore, it is not appropriate to evaluate with a single indicator. However, based on some objective data, it is possible to promote skill improvement by giving feedback to the subject. This research is one of the case studies.

We propose and implement a method for evaluating the discussion ability of students in meetings in a university laboratory setting. There are roughly three kinds of evaluation methods:
(1) One based on acoustic information, that is, the manner of speaking.
(2) One based on language information, that is, the contents of speech.
(3) One based on mental state, that is, a speaker's psychophysiological information, such as heart rate.

Method (1) evaluates the appropriateness of utterances in a discussion by using the acoustic characteristics of speech. The characteristics are automatically evaluated in real time and fed back to speakers during a meeting. For example, we measure the voice size (loudness), voice intonation, speech speed, fluency, tempo, and other vocal aspects of a speaker and automatically evaluate the acoustic appropriateness of the statements. If anything is determined to be inappropriate, the system provides feedback to the speaker in several ways, such as with a message popping up on a screen. Method (2) analyzes linguistic characteristics in consideration of context. For example, we estimate the consistency of the context of statements by using machine learning techniques. Then, the linguistic appropriateness of the statements is automatically evaluated. Method (3) estimates the degree of self-confidence of speech by measuring the heart rate while speakers participate in question-and-answer sessions. In addition, we check whether there is a correlation between the degree of confidence and the appropriateness of statements. Then, we evaluate the mental appropriateness of the statements.

We believe that carefully examining these three methods over a period of time will result in a more

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detailed analysis that helps us focus on more appropriate training for students.

Students' improvement in discussion ability is evaluated in subsequent training. Discussion-skill training is carried out through a repeat cycle that consists of notifying a person of a problem and giving advice via e-mail prior to a meeting, evaluating statements during the meeting, and the person reflecting and making improvements after the meeting.

2 DISCUSSION MINING

Seminar-style meetings that are regularly held at university laboratories are places where exchanges of opinions on research occur. Many comments on future work are included in the meeting records. However, as discussions at meetings are generally not recorded in detail, it is difficult to use them for discovering useful knowledge. Our laboratory developed and uses a discussion mining (DM) system that records the content of face-to-face meetings while providing metadata (Nagao et al., 2004). Looking back on the challenges presented in remarks is essential for setting new goals in activities, but their existence may be buried in many other remarks in the minutes.

In our laboratory at Nagoya University, we have used this DM system to record detailed meetings in the laboratory for over 10 years. The system enables all participants to cooperate together to create and use structured minutes. It is not fully automated, i.e., a secretary manually writes down the contents of speech, and each speaker tags his/her speech. Therefore, we can generate data with high accuracy.

The meeting style supported by the DM system is one in which a presenter explains a topic while displaying slides, and Q&A with the meeting participants is either conducted during or at the end of the presentation.

Specifically, using multiple cameras and a microphone installed in a discussion room, as shown in Figure 1, and a presenter/secretary tool we created, we record discussion content. In the center of the discussion room, there is also a main screen that displays presentation materials and demonstration videos, and on both sides, there are subscreens for displaying information on and images of the participants who are currently speaking.

The DM system records slide presentations and Q&A sessions including participants while segmenting them in time. As a result, content (discussion content), as shown in Figure 2, is recorded and generated.

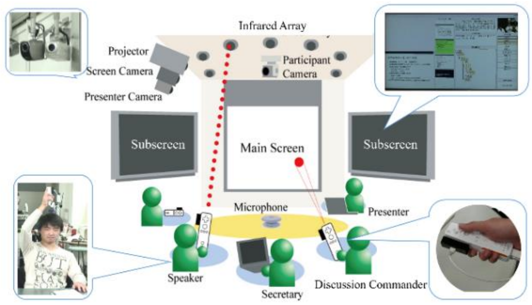


Figure 1: Overview of discussion mining system.

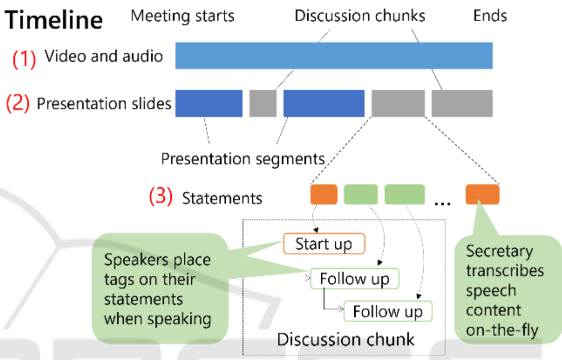


Figure 2: Structured discussion content.

Every participant inputs metadata about his/her speech by using a dedicated device that is called a "discussion commander," as shown in the lower right of Figure 1. Participants who specifically ask questions or make comments on new topics assign start-up tags to their statements. Also, if they want to speak in more detail on topics related to the immediately preceding statement, they provide a follow-up tag. Furthermore, the system records pointer coordinates, the location of figures and texts in a slide, and information on a button pressed to indicate that one is for or against a statement during a presentation and Q&A session. Information marked on important statements is also recorded.

We also developed a system for searching and viewing recorded data. In this system for browsing discussion content, a user can search the contents of an agenda from a date and participant information, view past discussions similar to the ongoing debate, and effectively visualize the state of a discussion.

In addition, we also focus on pointing and "referring to" behaviors during meetings. Speakers usually refer to something when making a statement, e.g., "this opinion is based on the previous comment" or "this is about this part of the slide" (while pointing to an image or text in the slide). We assume that a statement with a reference to an object in a slide is strongly related to the topic corresponding to the object. We also assume that two statements during which the speakers point to the same object are about the same topic. Therefore, we concluded that acquiring and recording information on pointing to objects in a slide would facilitate topic segmentation and lead to more precise semantic structuring of discussions. We call an object pointed to in presentation material a "visual referent." We thus developed a system for pointing to and selecting objects in slides that uses the discussion commander mentioned earlier and created a mechanism for acquiring and recording information on pointing to objects in relation to participants' statements.

This system can also extract any part of a figure in a slide and refer to it. In addition, selected or extracted image objects can be moved and magnified by using the discussion commander.

3 DISCUSSION-SKILL EVALUATION

As explained in the previous section, the DM system we developed records the statements of each participant during a meeting as the discussion content, including video/audio data and text minutes. Therefore, we can automatically evaluate statements on the basis of their acoustic features and linguistic features.

In addition, considering that the discussion process is a type of cognitive activity, which could result in changes in certain psychophysiological data, such as heart rate (HR) variability (HRV), several studies have proven that HR is an important index of the autonomic nervous system regulation of the cardiovascular system (Camm et al., 1996). Therefore, there has been increasing focus on observing the correlation between HR data and cognitive activities. A study on measuring the HR during three cognitive tasks (Luque-Casado et al., 2013) revealed the affection of cognitive processing on HRV. The stress level also has been assessed during Trier social stress test tasks, a type of cognitive activity, by using HR and HRV metrics (Pereira et al., 2017). Judging from the large amount of evidence presented, we argue that the HR data of the participants of a meeting can be used to effectively evaluate the answer-quality of Q&A segments, which is helpful in improving participants' discussion skills (Peng and Nagao 2018).

3.1 Acoustics-based Method

At a meeting, participants need to discuss a topic, analyze the meaning of other people's statements, and communicate their argument in an easy-to-understand manner. "Voice size," "speech speed," "pause," "conciseness" etc. are mentioned as ways of making speaking easy-to-understand (Kurihara et al., 2007). On the basis of this, we set eight evaluation indicators based on acoustic features and based on linguistic features.

The indicators that are used to evaluate only acoustic features are as follows.

A. Voice Size: voice should be large enough for a speaker to be heard, while it is better for it to not be too emotional and too big. Therefore, we measure and evaluate the volume [dB] of each statement being uttered.

B. Voice Intonation: speech without intonation is a factor that makes a listener bored. We measure the height of a voice in a statement (fundamental frequency F0, described later) [Hz] and evaluate the statement with high standard deviation values used to indicate a good evaluation.

C. Speech Speed: a statement will be hard to hear if it is too fast or too slow. Therefore, if the speech speed [the number of syllables per hour (syllable is described later)] is within an appropriate range, it is evaluated as good.

D. Fluency: speech with a lot of silence and disfluency is difficult to understand. A good evaluation is given to statements with few filled pauses (vowel extensions), such as "eh" during speaking and few periods of silence of more than two seconds.

E. Tempo: it seems easy to understand speech when emphasized parts are clear. It is effective when statements are not monotone, such as when a person speaks slowly a part that they want to emphasize and sets a pause before the emphasized part. Therefore, the tempo of a statement is evaluated on the basis of the standard deviation of the speech speed and the number of "pauses" ("pause" is defined as a period of silence of less than 2 seconds).

Here, the fundamental frequency (generally written as F0) is a value expressing the periodicity of sound, which is the acoustic feature quantity that governs the pitch of sound. There is periodicity in voiced sound (vibrating of the vocal cord), so the reciprocal of that period (basic period) is the fundamental frequency.

F0 is a very important index that considers the intonation of voice, but its accurate extraction is very difficult for the following reasons: (1) a speech waveform is a quasiperiodic signal (due to the quasiperiodicity of vocal fold vibration), and periodicity is not clear, (2) speech is mixed with noise, and (3) the range of change in F0 in voiced sounds is difficult to limit because the range is wide. Accurately extracting F0 is very difficult. Therefore, several estimation methods have been proposed. An acoustic analysis program called "Speech Signal Processing Toolkit" (SPTK) was released (http://sp-tk.sourceforge.net/), in which an algorithm called "pitch extraction" is implemented to estimate F0.

In addition, the syllable used to calculate the speech speed is a type of segmental unit that separates consecutive voices and is a group of sounds heard. Typically, it is a voice (group of voices) consisting of one vowel and its vowel alone or with one or more consonants before and after the vowel. In the case of Japanese, syllables may use a segmental unit called a "mora" (beat) that does not necessarily agree with the syllable. Strictly speaking, the mora is used instead of a syllable. The main difference between a syllable and mora is that a long vowel, geminate consonant, and syllabic nasal are integrated with the preceding vowel in the case of a syllable, but, in the case of the mora, it is one mora.

3.2 Linguistics-based Method

Next, evaluation indicators based on linguistic features are as follows.

F. Conciseness: it is easier to understand a statement if it is concise. Therefore, for the sake of evaluating conciseness, we compare the number of syllables of statements (strictly mora) in a meeting obtained by speech recognition and the number of syllables of the corresponding statements in the minutes of the meeting. Since a secretary describes the content of the statements in a summary, if the number of syllables of the statements and number of syllables of the corresponding statements of the minutes are close, the statements can be regarded as concise.

G. Relevance to Topic: statements should be relevant with the subject of discussion as much as possible. If the content of follow-up statements has much in common with the content of a topic-raising statement, i.e., start-up statement, the statements can be regarded as relevant with the theme. Therefore, by evaluating the degree of relevance with start-up statements (described later), the relevance of statements is evaluated.

H. Consistency of Context: follow-up statements need to be coherent or consistent with their parent statements. In other words, the content of a follow-up statement and the content of its parent statement must be semantically related, so it is important to evaluate the degree of consistency. We use a machine learning technique to judge whether a statement is consistent and decide the evaluation value on the basis of the judgment. The technique is described later.

We calculate the degree of relevance between statements in the following way. First, we calculate the term frequency (TF)-inverse document frequency (IDF) values of words in each statement by using the following formula.

$$tfidf_{i,j} = tf_{i,j} \cdot idf_i$$

$$tf_{i,j} = \frac{n_{i,j}}{\sum_{k \in T} n_{k,j}}$$

$$idf_i = \log \frac{|D|}{|\{d : d \ni t_i\}|}$$

Here, $n_{i,j}$ is the number of occurrences of word t_i in document d_j. $\sum_{k \in T} n_{k,j}$ is a summation of the number of occurrences of all words in document d_j (T is the set of all words). $|D|$ is the number of all documents, and $|\{d : d \ni t_i\}|$ is the number of documents that contain word t_i.

IDF works as a kind of general language filter. If words (generic words) appear in many documents, their IDF values decrease. If words appear only in specific documents, their IDF values rise.

Using the TF-IDF value with each statement of one meeting as one document, we weight the word t with the following formula to obtain the degree of relevance.

$$f(t, d_1, d_2) = \left(\frac{tf(t, d_1)}{\sum_{s \in d_1} tf(s, d_1)} + \frac{tf(t, d_2)}{\sum_{s \in d_2} tf(s, d_2)} \right) \cdot idf(t)$$

For words that appear commonly in two documents, add that value, subtract the value for words that appear only on one document, and sum over all the words. Let this value be the degree of relevance between statements.

Additionally, it can be said that inconsistent statements in a discussion are statements that describe topics that are different from topics up to that point. Therefore, we need to consider how to categorize follow-up statements as statements deviating from topics or not. Logistic regression analysis is used for this classification. In this case, we calculate a probability value that measures how much a statement deviates from a topic and use this value to evaluate the consistency of the statement. For this purpose, in addition to the linguistic features obtained from the minutes, we use the meta-information given in the minutes. The features used in this method are as follows.

(1) Features based on linguistic features of statements

- Relevance to parent statement
- Number of sentences of statements
- Number of characters of statements

- Morpheme unigram and morpheme bigram
- Presence of subject word and referring word
- Entity grid

(2) Features based on meta-information attached to the minutes

- Whether a speaker is a student, whether it is a presenter
- Whether the speaker of the parent statement is the presenter
- Presence of marking/agreement/disagreement buttons
- Depth from the root in a tree structure (i.e., discussion chunk)
- Whether the visual referent of the parent statement matches that of the target statement
- Presence or absence of slide use during speaking
- Time at which speaking is reserved
- Presence or absence of different statements in a time series between the parent statement and the target statement
- Alternating of questioners

For morphemes and morpheme pairs that appear during speech, the number of occurrences of nouns, verbs, adjectives, auxiliary verbs, and morpheme pairs is calculated with a preliminary survey. We use those that exceed a certain value for the morpheme unigram and bigram features. Also, since there is a report that states that an entity grid is effective for evaluating text consistency (Barzilay and Lapata 2008), we applied it to evaluate the transition in themes and used the transition probability of a certain syntactic role of the grid for the feature. The selected syntactic role is directly related to topic transition. The alternating of questioners, which is the last feature, means whether a questioner is different from that of the preceding statement pair when considering a participant's question and presenter's response as a statement pair.

We implemented the above method and conducted an experiment on discriminating inconsistent statements. As a data set, we used 53 minutes (discussion content) of a seminar in our laboratory (number of statements: 3,553). However, since start-up statements were not subject to this case, follow-up statements (number of statements: 2,490) were subject to discrimination. As correct-answer data (teacher signals), we manually decided whether a certain statement lacked consistency and gave the attribute of inconsistency to the statement. 202 follow-up statements were determined to be lacking in consistency.

To evaluate the proposed method, a case in which learning was carried out without using features based on the meta-information of the minutes was taken as a comparative method. For the evaluation, we used the precision, recall, and F1 score, which is a harmonic mean of these two values, and also carried out a 10-fold cross validation.

The results of this experiment are shown in Table 1.

Table 1: Experimental results for consistency judgment.

	Precision	Recall	F1 score
Proposed method	0.269	0.534	0.358
Comparative method	0.117	0.129	0.123

The results of judging consistency with the method we proposed were higher than the case where the feature information given to the minutes was not used, for each precision, recall, and F1 score. The advantage of the proposed method was confirmed.

In addition, when classification learning by removing each feature of the meta-information of the minutes, the precision, recall, and F1 score decreased for all the features, and the used features described above were confirmed to be effective. Table 2 shows the results of the top five cases where the F1 score dropped greatly.

Table 2: Feature contribution to learned model.

Removed feature	Precision	Recall	F1 score
Whether speaker is presenter	0.255	0.494	0.337
Presence of marking/agreement/disagreement buttons	0.251	0.522	0.341
Depth from root in tree structure (i.e., discussion chunk)	0.253	0.522	0.341
Whether visual referent of parent statement matches that of target statement	0.259	0.506	0.342
Alternating of questioners	0.255	0.534	0.345

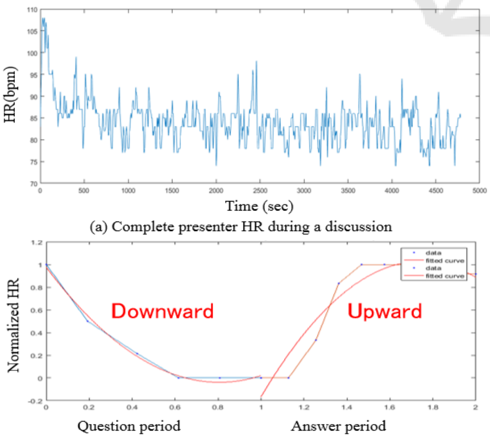
3.3 Psychophysiology-based Method

Smart watches, such as Apple Watch, the Fitbit series, and Microsoft Bands, contain wearable sensors to accurately detect users' biological data, such as HR and blood pressure. Such non-invasive detection makes it possible to link users' biological information with their daily activities. Iakovakis and Hadjileontiadis (2016) used Microsoft Band 2 to acquire the HR data of users to predict their body postures. In our study, we used Apple Watch to collect participants' HR data on the basis of our DM system and to visualize the data during discussions. Through the Health Kit framework on Apple Watch, which we asked participants to wear on their left wrist during discussions, participants' HR data were acquired almost in real time in 5–7 sec intervals, as shown in Figure 3. The collected HR and participants' information is displayed on the Apple Watch screen as well as synchronously presented on an HR browser.

Figure 3: HR acquisition system.

To automatically evaluate the discussion performance, we started from analyzing the answer-quality of Q&A segments, which are the most important constituent components generated around a discussion topic. Our goal was to validate our argument that the HR of discussion participants can be used to effectively evaluate the answer-quality of Q&A segments during discussions.

All HR information of participants during their discussions is displayed in a graph, shown in Figure 4 (a), that presents a participant's complete HR detected per minute throughout a discussion. The HR segments in each Q&A segment were then extracted and displayed in a graph, shown in Figure 4 (b), which shows HR data during a question period (blue line) and answer period (orange line). We then computed 18 HR and HRV features from all Q&A segments as well as the question and answer periods separately.



(a) Complete presenter HR during a discussion

(b) HR trend during question and answer period

Figure 4: HR acquisition system.

The HR and HRV features include mean, standard deviation (std.), and root mean square successive difference (RMSSD) from these two periods (question and answer periods), and these metrics have been proven to be important for understanding HRV differences under cognitive activities (Wang et al. 2009). The trends in the HR of these two periods are also computed by calculating the difference between two adjacent HR points. If the number of positive differences was more than the negative ones, we assumed that the HR period showed an upward trend; if not, it showed a downward trend, as shown in the Figure 4 (b). We used a quadratic curve (red line) to more clearly present the HR trend. We can see that HR during the question period showed a downward trend and upward trend during the answer period.

We also divided the HR data of these two periods into nine ranges: less than 60 bpm, 60–70 bpm, 71–80 bpm, 81–90 bpm, 91–100 bpm, 101–110 bpm, 111–120 bpm, 121–130 bpm, and more than 130 bpm. The mean and std. were calculated to describe the HR appearance-frequency distribution in each range. Table 3 summarizes these 18 features.

Table 3: HR and HRV features.

HR period	HR and HRV features
Both periods	mean, std., RMSSD, trend,
	freq. all mean, freq. all std.
Question period	mean, std., RMSSD, trend,
	freq. question mean,
	freq. question std.
Answer period	mean, std., RMSSD, trend,
	freq. answer mean,
	freq. answer std.

We collected discussion data from 9 presenters from 9 lab-seminar discussions held over a period of 4 months. Twelve undergraduate and graduate students and 3 professors made up the participants. The discussions were carried out following the presenters' research reports, with the participants asking questions related to the discussion topic that were then answered by the presenters. There were 117 complete Q&A segments extracted from these 9 discussions, and the answer-quality of these Q&A segments was evaluated by the participants who asked the questions by giving a score based on a five-point scale: 1 = very poor, 2 = poor, 3 = acceptable, 4 = good, 5 = very good. We obtained 66 high-quality answers with scores from 4–5 and 51 low-quality answers with scores from 1–3.

We adopted three machine learning models, logistic regression (LR), support vector machine (SVM), and random forest (RF), to carry out binary classification of the Q&A segments' answer quality. About 80% of Q&A segments were randomly selected as a training data set and the remaining 20% as a test data set.

For the LR model, we obtained a 0.790 F1 score by using an eight-feature candidate subset and an F1 score of 0.740 by using a seven-feature candidate subset; therefore, we used the eight-feature subset to train our LR model. We obtained an F1 score of 0.805 for the SVM model with 10 HR and HRV features we selected in advance. For the RF model, when there were 36 trees (submodels of RF) and 19 terminal nodes on each tree, we obtained the highest F1 score of 0.87. In this case, we chose an eight-feature subset. Table 4 lists the evaluation results for each model.

Table 4: Evaluation results of each learning model.

Evaluation model	F1 score
Logistic Regression (LR)	0.790
Support Vector Machine (SVM)	0.805
Random Forest (RF)	0.870

Comparing the F1 scores of each model, the RF model exhibited superior evaluation performance compared with the LR and SVM models. Considering all three models, the HRV data of participants showed an outstanding performance in evaluating Q&A segments' answer quality. Meanwhile, we focused on seven HRV features: all mean, answer trend, all RMSSD, freq. answer std., answer std., question trend, and all trend, which exhibited the largest effect on all three models.

Our evaluation method automatically evaluates all statements of meeting participants by using the evaluation indicators mentioned above. Let the weighted average value of the value of each indicator be the evaluation of one statement, and let the sum of the evaluation values of all statements of a participant be the numerical value expressing that participant's speaking ability in discussions at a meeting. By looking at the changes for each discussion in each meeting, participants will be able to judge whether their discussion skills are rising or stagnating.

4 FEEDBACKS OF EVALUATION

The evaluation indicators as described in the previous section are indices for measuring participants' discussion ability, but, of course, they should be used not only for measurement but also for extending their ability. One way to do this is to visualize the results in an easy-to-understand manner and feed them back to the participants at just the right time.

Participants should make an effort to raise their discussion ability. For that purpose, the system we developed evaluates their statements during a meeting, points out the problems, and encourages improvement. There are various ways to point this out. One is to display a message on the main screen during or shortly after speaking or to display icons next to the name of each participant in the member table of the sub-screen. There is another way to display feedback including somewhat detailed information, that is, with the icons and their descriptions shown on the tablets used by all the participants.

We previously implemented a mail notification mechanism in order to let participants know that the minutes were completed and accessible. Apart from that, this time, we added a mechanism to notify participants of the result of evaluating the statements at the last meeting and the points to be paid attention to in the next meeting by e-mail.

4.1 Real-time Feedback

The evaluation indicators using the acoustic features described in the previous section can be used to automatically calculate the evaluation values and feedback during a meeting. Specifically, they are used to evaluate in real time the "voice size," "voice intonation," and "speech speed," and when a value is lower than a certain threshold value, that is, a "bad" evaluation value, the system pops up a warning message immediately on the main screen (normally displaying presentation slides) as shown at the bottom right of Figure 5. This display will be hidden after 2 seconds.

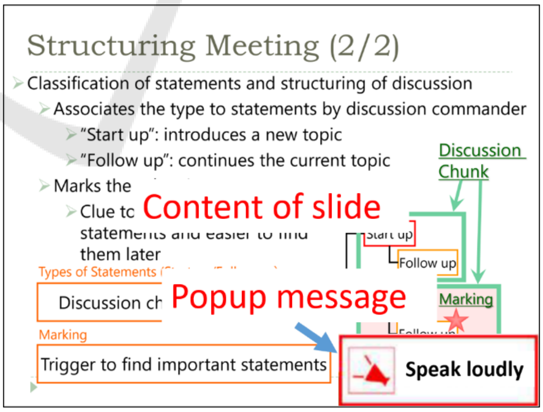


Figure 5: Feedback message appearing on main screen.

To measure the effect of this simplest direct feedback on participants, we evaluated the participants' "voice size," "voice intonation," and "speech speed" at five meetings. The results of examining the change in evaluation values are shown in Table 5. For "voice size," the message to be displayed differs depending on whether the evaluation value is smaller or smaller than a reference value. "Speech speed" may be faster or slower than the reference value, but in the preliminary experiments, it was extremely rare for it to be slower than the reference value, and it was overwhelmingly faster in the faster case. Only when the evaluation value was larger than the reference value was the message displayed.

Table 5: Experimental results of effects of feedback on main screen.

Evaluation indicator	Message	No. of displays	No. of improvements	Improvement rate
Voice size (small)	Speak loudly	32	27	0.84
Voice size (large)	Calm down	5	4	0.80
Voice intonation	Speak with inflection	30	20	0.67
Speech speed	Speak slowly	67	44	0.66

4.2 Mail-based Feedback

Although it seems that there is an immediate effect from the feedback of evaluation results during the meeting, it may be difficult for participants to continue speaking at the next meeting as they may be conscious of their weaknesses pointed out last time. That is because participants are not always trying to improve their discussion skills, and they have to pay attention to other issues to be considered among meetings, e.g., achieving tasks.

For this reason, a mechanism for reminding students of the problems in statements made at the last meeting is required. Of course, if a student reviews the minutes, he or she can reconfirm the evaluation results of the statements as well as the contents of the previous meeting, but it is unlikely that he/she will frequently review the minutes unless the agenda is very important.

Therefore, we implemented a mechanism for notifying participants of the result of evaluating statements made at the last meeting and the points to be paid attention to in the next meeting by e-mail. An example of a notification mail is shown in Figure 6. This is called "HTML mail," and the receiver can display the contents, including images and links to Web pages, in the mail application. The sentences and graphs shown in Figure 6 were automatically generated on the basis of discussion data. Compared with the evaluation results of the previous meetings, the mail contains commentary on the items that show little improvement while referring to the data.

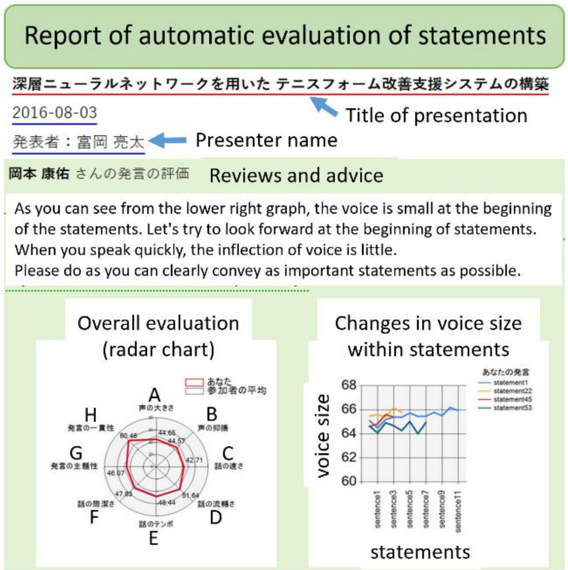


Figure 6: Example of notification mail.

4.3 Generating Reviews and Advice

To generate reviews and advice, the degree of deviation from the mean evaluation value of a participant's whole statements is used as a score. Our proposed mechanism compares scores and considers the indicators with lower scores as discussion skills that should be improved on by the participants, and it generates a review/advice text that encourages them.

The review/advice content consists of meeting information, sentences representing evaluation, and graphs, as shown in Figure 6. The meeting information describes the title of the meeting, the date and time, and the presenter. Also, a comprehensive evaluation and an individual evaluation corresponding to a sentence to be presented are graphically displayed.

The review/advice text is created by generating sentences for each evaluation indicator and combining those sentences. Each sentence element is weighted, and a sentence having the maximum overall weight is generated under the constraint of the length of the total text.

An overview of the evaluation of the statements can be seen in the graph (radar chart) of the comprehensive evaluation. However, to improve participants' discussion skills, more specific factors need to be presented. For this purpose, the evaluation results for indicators are analyzed on the basis of time and relationship to other indicators. Specifically, the analysis is performed by taking into consideration the relevance to other evaluations, such as the time division, for example, a small voice at the beginning of statement or no intonation when the voice is large. The sentences are generated on the basis of a more situated evaluation.

The text of the review/advice is composed of three types of sentences, as shown in Table 6. Factual sentences describe the evaluation results and inform participants of the current situation. Advice sentences describe methods for improving on bad evaluation results for discussion skills. Encouragement sentences motivate participants to improve their discussion skills by describing the importance of the evaluation indicators to be improved on and by encouraging the participants to improve.

Table 6: Sentence element per sentence type.

Sentence type	Sentence element
Factual	rationale, temporal situation, relevance to other evaluations, content of evaluation
Advice	temporal situation, relevance to other evaluations, advice
Encouragement	importance of indicator, excitation

A sentence is composed of several sentence elements. An example of a generated factual sentence is shown in Figure 7. Sentence elements are selected one by one from the rationale, temporal situation, relevance to other evaluations, and content of evaluation indicated in red. Sentence elements are selected at this time on the basis of the weighting of the sentence element and the maximum length constraint of the total review/advice text.

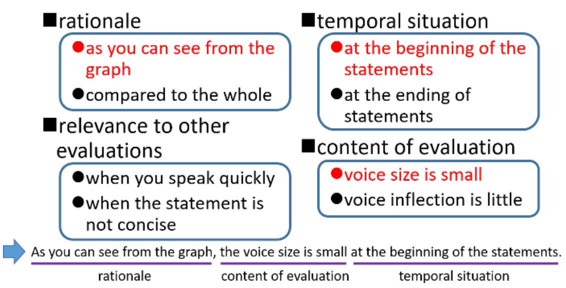


Figure 7: Example of factual sentence generation.

The review/advice text should describe the evaluation indicators with low values and increase the weight of sentence elements related to the results. If the same sentence elements are repeatedly selected, the effect of the review may be diminished, so we reduce the weight of sentence elements that have already been presented.

On the basis of the above consideration, the weight $c(e_i)$ of a sentence element e_i can be expressed as follows by using the score $S(e_i)$ of e_i, the degree of the relevance $R(e_i)$ between an evaluation indicator and sentence element, and a value indicating a past presentation state $P(e_i)$.

$$c(e_i) = S(e_i) \times R(e_i) \times P(e_i)$$

The generation mechanism solves the following integer programming problem with the maximum length L_{max} of the total review/advice text and selects sentence elements as the solution $\{x_i\}$ of the problem.

$$max: \ \sum_i c(e_i)x_i$$
$$subject\ to: \ \sum_i l(e_i)x_i \leq L_{max}$$
$$x_i = \{0,1\}$$

Here, $l(e_i)$ is the character string length of a sentence element e_i.

5 REMAINING ISSUES

To train the discussion ability, it is necessary to record evaluation results over a considerably long span of time. Changes in short-term evaluation results are effective as a clue to evaluating and improving the performance of the developed system, but this will not be enough to judge whether a person certainly has improved their discussion ability. This is similar to the fact that local optimal solutions do not necessarily become true optimal solutions when optimizing the parameters of machine learning models.

It is often said that human education takes time. We think that discussion skills as well as basic academic ability need to be firmly acquired over the long term. To that end, we believe that we must have a clear guide that becomes a signpost. Without good, clear, and factual guidance, people will lose confidence in themselves. The system for acquiring and evaluating data that we developed is useful for clarifying what can be done to improve what kind of ability. We believe that "evidence-based education" (Nagao et al. 2017) will be possible with such a mechanism.

We believe that discussion ability is a fundamental and important skill that human beings use to perform intellectual activities. Improving this ability is a task that can be said to be essential for many people. However, if visible growth does not appear, people will get bored with such training. We are planning to introduce gamification techniques to solve this problem.

6 CONCLUDING REMARKS

We proposed a method for automatically evaluating statements and a feedback system for the purpose of improving the discussion skills of participants at meetings. For automatically evaluating statements, we set five evaluation indicators based on acoustic features: voice size, voice intonation, speech speed, fluency, and tempo. We also set three evaluation indicators based on linguistic features: conciseness, relevance to topic, and consistency of context.

We also argued that participants' heart rate (HR) data should be taken advantage of to effectively evaluate the answer-quality of Q&A segments in discussions. We developed a system for acquiring heart rates on the basis of a discussion mining (DM) system with the help of a non-invasive device, i.e., Apple Watch, worn by participants. To verify our argument, we generated 3 binary classification models for evaluation, logistic regression, support vector machine, and random forest, and selected the 7 most meaningful features out of all 18 HR and HR variability features.

Next, we analyzed the result of automatically evaluating discussion skills and proposed a mechanism for generating review and advice text using sentences and graphs on the basis of the values of indicators of discussion ability. In the analysis on automatic evaluation, temporal situation, relevance to other evaluations, and comparison with past results were considered. Also, to encourage participants to improve their discussion skills, sentences in review/advice text were categorized into three types: factual sentences, advice sentences, and encouragement sentences. We also collected the sentence elements of these sentences, and the review/advice generation mechanism set weights to them in consideration of the relationships between the evaluation indicators and the sentence elements and the past presentation situation. The mechanism generates sentences so as to maximize the weight of the elements. The generated sentences and graphs are optimum for improving discussion skills. We confirmed that the review/advice text can express the evaluation results appropriately and is effective for improving the discussion skills of participants.

Future tasks include long-term participant-based experiments on evaluating discussion skills and on training and on extending the training process to motivate students to continue training on the basis of gamification techniques (Ohira et al. 2014).

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