Enhancement of Creative Aspects of a Daily Conversation with a Topic Development Agent

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Abstract. Daily informal conversations are highly creative activities. However, it is hard for most ordinary creativity support systems and discussion support systems to deal with daily conversations because they are done in environments characterized as free. In this paper, we propose a topic-development agent that is adaptable to daily conversations and that enhances the creative aspects of the conversations by entering them as an equal participant with the human participants and keeping the conversation lively. This agent autonomously detects novel directions in which new topics can be developed in conversations, and provides a piece of information which can likely form the seed of a new topic. From the experimental results, it is suggested that this agent can provide timely information to introduce a new topic and that the agent has the ability to effectively coordinate the creative aspects of daily conversations.

1 Introduction

A daily informal conversation can be a very creative activity. More specifically, we can obtain not only new information but also new ideas, inspirations and clues for solving difficult problems in a daily conversation with colleagues or friends. In this paper, we describe an agent that participates in on-line conversations as a normal participant, not as a moderator, and activates the conversations in order to enhance their creative aspects.

A daily conversation can be regarded as a mixture of divergent thinking and convergent thinking, which are two of the significant, but usually not distinguished, processes involved in human creative thinking [1]. Namely, in such a conversation, various pieces of information are first provided as the utterances of the participants (i.e., the divergent stage). Then, if a participant finds some relevance among some of the information or between some of the information and the participant's own knowledge (i.e., the convergent stage), the participant provides a new topic based on that relevance. Thus, the conversation progresses to a new phase, and this continues by alternating the divergent and convergent stages. Both the divergent thinking and the convergent thinking are done more deeply and broadly in lively conversations where many participants provide many utterances. Therefore, the creative aspects of conversations are especially remarkable in lively conversations.

Several CSCW systems which support the creative aspects of discussions have been developed. Such systems usually impose some special restrictions (or certain special attitudes) on the users. For instance, gIBIS [2] requests users to always declare the position of each utterance: support, objection and so on. DOLPHIN [3] requests users to group all of the opinions and to arrange the groups in a tree structure. Such requirements induce the effectiveness of the systems. On the other hand, however, the requirements isolate the system tasks from daily routine work and make it difficult for people to use the systems. Recently, to tackle this problem, it has been pointed out that creativity support systems should be more intimately linked with daily routine work and daily activities [4]. In particular, focus has been placed on daily conversations which are found in environment with a lot of freedom and few restrictions.

Hence, in order to support daily conversations, we should eliminate unusual restrictions as much as possible. Therefore, an agent named "conversationalist", which is described in this paper, was developed to play the role of a general participant, not a moderator. We think that the existence of a moderator causes a different atmosphere from that of a daily conversation. The agent supports the creative aspects of a conversation by autonomously providing pieces of information that might form the seeds of new topics; these pieces are normal utterances based on the situation of the conversation and the agent's own viewpoint. Boden pointed out that transformation of a conceptual space and exploration within the space are fundamental to human creativity, and that an agent can effectively help in this transformation and exploration [5]. The agent we describe in this paper supports humans in transforming and exploring the conversation space.

Section 2 describes conversation model which we assume in order to construct the conversationalist. In section 3, we mention the strategy to keep conversations lively. Section 4 describes the implementation of the conversationalist in detail. Section 5 shows an experimental conversation with the conversationalist and discusses the results. Section 6 shows methods to create conversation support agents with various characteristics. Section 7 gives brief conclusion and shows the future works.

2 Conversation Model

Since this research deals with daily conversations, neither the number of participants, nor the domains of topics are restricted, and the goal of a conversation need not be evident. We assume only the following conditions:

1. **A two-level structure of topics**
   We assume there are two levels of topics in our target conversation: a global topic and local topics. The global topic persists through the whole conversation, and each local topic is a partial topic under the global topic. A conversation, therefore, consists of successive local topics. It is assumed that a local topic does not have sub-topics.
2. **Cooperative conversation transition control**
   In a daily conversation (without a moderator), it often happens that a partic-

ipant leads the conversation by focusing on a certain topic, and if the seed of a new topic is provided by another participant and the new topic is accepted by the others, a topic transition occurs and the participant who provided the new topic leads the conversation. Thus, we can regard all of the participants as cooperatively and individually watching and controlling the conversation transitions by successively taking turns as leader. Moreover, this cooperative work emerges nonintentionally. Each participant indirectly controls the conversation by providing pieces of information as normal utterances, not utterances for explicitly controlling the directions of the conversation.

Note that users need not be conscious of the assumptions in conversations with the conversationalist. There is no problem for users to use the conversationalist even if they think there is a nest-structure of topics in a conversation, or even if they have no idea about conversation transition mechanisms. The assumptions are needed only for the conversationalist to grasp the situation of a conversation and to decide how to act in each situation. Therefore, the assumptions do not obstruct the features of daily conversations, i.e., freeness and non-restrictiveness.

3 Strategy To Activate A Conversation

At least the following two conditions can be regarded as characteristics of a lively conversation:

1. Topics change often enough, and
2. Topics are compatible with the participants' interests.

The conversationalist always intends to ensure these two conditions.

To ensure that topics change often enough, the conversationalist always monitors the transition of topics. When a standstill is detected, the conversationalist intervenes in the conversation and provides a piece of information that can form the seed of a new topic.

To ensure that the introduced topics are of interest to the participants and to obtain information to help introduce new topics, the conversationalist continuously monitors the development structure of the topics. This structure effectively reflects the participants' interests. It is not good enough, however, for the extracted pieces of information to be only those directly relevant to the current topics. Such information does not help to change the topics but instead allows the conversation to stagnate. In order for the topics to change, some novel information must be introduced. Therefore, the conversationalist was developed to offer its own viewpoint. Consequently, it indicates novel directions of topic development by retrieving information based on both the development structure of topics and its own viewpoint.

4 Implementation

In this section, we describe the details of the implementation of the conversationalist. Since a daily conversation is not always well-structured and, moreover, it often spreads over several domains, it is not realistic for the conversationalist to have frame-knowledge of the conversation transitions or contents beforehand. Therefore, we apply a method of processing a conversation based on the surface information of each utterance.

Figure 1 shows the software structure of the conversationalist. The utterance-processing module morphologically analyses each input utterance and extracts weighted keywords by regarding the history of each keyword in a conversation. The conversation-structuring module arranges each utterance and keyword in 2-dimensional space based on a statistical method. Then the topic-development-recognition module searches for main topics and empty spaces in topics by using the space obtained by the conversation-structuring module based on an image processing method. On the other hand, the topic-transition-observation module observes topic transition by evaluating cohesion among utterances. If stagnation is detected in a topic, the topic-seeds-provision module is invoked and a piece of information is extracted which can form the seed of a new topic based on the topic development situation obtained by the topic-development-recognition module.

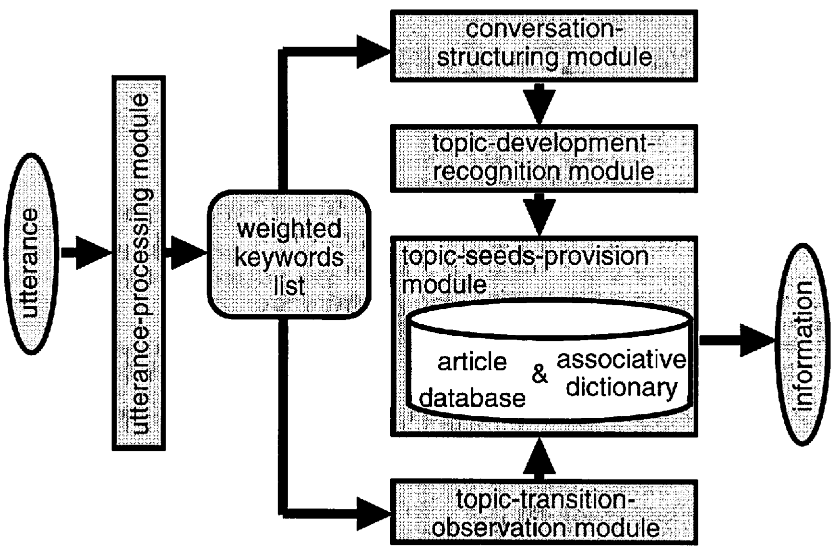

Fig. 1. Software structure of the conversationalist agent.

4.1 Utterance-Processing Module

The input data are the human participants' utterances as text data. We call the text data of each utterance an "utterance-object." This module analyzes an input utterance-object morphologically and determines the part-of-speech of each word. Nouns and unknown-part-of-speech words are then extracted as keywords of the utterance-object.

The weight $W_{w_i,n}$ of the keyword w_i at the n-th utterance is calculated by the following equation:

$$W_{w_i,n} = \frac{(1+\frac{1}{1+e^{-f_{w_i,n}+F_l}})(1+\frac{1}{1+e^{-i_{w_i,n}+I}})}{(1+\frac{1}{1+e^{-f_{w_i}+F_g}})^2}, \quad (1)$$

where f_{w_i} is the number of utterance-objects that include the word w_i until the $(n-1)$-th utterance-object, $f_{w_i,n}$ is the number of the word w_i in the n-th utterance-object, and $i_{w_i,n}$ is the blank duration in terms of the number of utterances made since w_i appeared last. The terms F_g,F_l, and I are constants, and their respective empirical values are 5,1, and 10. The weghting policy is as follows: A keyword appearing frequently throughout an entire conversation is a very general word used in all kinds of conversations, or a word related to the global topic of the conversation. Therefore, such words are not important for the utterance-object and weighted lightly. On the other hand, a keyword frequently used in a certain utterance-object and a keyword appearing in an utterance-object after a long unused period (or a first-appearing keyword) is important for the utterance-object, even if the word frequently appears throughout the whole conversation. Therefore, such words are weighted heavily.

4.2 Conversation-Structuring Module

We used the thought-space structuring method of Sumi et al. [6], in which relations between concepts (i.e., utterance-objects) and elements of concepts (i.e., keywords) are represented by spatially arranging the concepts and the elements.

For this spatial arranging, we applied the dual scaling method, which is a multi-variant statistical analysis method and which provides principal components of given data[7]. When an object set that consists of plural quantification attributes is given, the dual scaling method represents the relations of the attributes shared among the objects and the co-occurrent relations among the attributes as spatial relative relations, by quantitatively grading the object set and the attribute set.

In this research, we regarded keywords which are automatically extracted by the utterance-processing module as attributes of utterance-objects and regarded the weight of each keyword as its attribute value. As a result, the conversation-structure space which represents the relations among all of the utterance-objects and all of the keyword-objects (a keyword-object consists of a unique keyword) was obtained.

4.3 Topic-Development-Recognition Module

The conversation-structure space obtained by the conversation-structuring module usually provides several clusters that consist of several utterance-objects. Since highly relevant objects are placed close to each other in the conversation-structure space, we can assume that a cluster corresponds to certain contents. Therefore, we can know what kinds of contents compose the conversation and what the main contents are from the conversation-structure space. On the other hand, there are often "empty spaces" where no utterance-objects exist in the conversation-structure space.

This module divides the conversation-structure space into 16-by-16 cells. The number of utterance-objects is counted for each cell by smooth filtering, and this is regarded as the weight of each cell. After each utterance, this module searches for peaks of cell weights, and regards the peak cells as the main contents. At the same time, the distance of each 0 weighted cell from the boundary of clusters of non-0 weighted cells and that of the conversation-structure space are calculated based on a Euclidean distance transformation method [8]. If there are any clusters of 0 weighted cells which exceed a threshold distance (currently, a distance of 2 cells), this module regards them as empty spaces of the conversation at that time and regards the most distant region as the main empty space.

4.4 Topic-Transition-Observation Module

This module detects topic transition points in real-time by using two kinds of utterance cohesion – micro cohesion and macro cohesion – obtained from the morphological data and time transition data of the utterances [9]. The micro cohesion is determined by whether or not several specific expressions (e.g., clue-words, indicate-pronouns, synonyms, antonyms) are included in an utterance. The micro cohesion quantifies the cohesion between an utterance and the utterance just before it: strongly connected, weakly connected, or strongly disconnected. The macro cohesion is determined by the frequencies and intervals of nouns and synonyms included in utterances, and by the time since the last topic transition occurred. The macro cohesion at each utterance quantifies the tendency to maintain the topic so far talked about. Topic transitions are detected at the following utterances:

1. Utterances where the micro cohesion indicates a strong disconnection and the macro cohesion is not so strong, or
2. Utterances where the micro cohesion indicates a weak connection and the macro cohesion is very weak.

Since this method does not need any data from utterances after the current utterance, topic transition points can be detected in real-time. As a result, conversation stagnation can be detected. In the current prototype system, conversation stagnation is detected when a topic transition does not occur within twenty utterances.

4.5 Topic-Seeds-Provision Module

This module is invoked when the stagnation of a conversation is detected in the topic-transition-observation module. This module has a text object database that consists of many text objects. Beforehand, keywords are extracted from each text object in the same way that the utterance-processing module extracts keywords. All of the keywords, however, are weighted equally. A keyword vector of a text object is generated from extracted keywords and it is stored with its text object in the text object database. A piece of information is retrieved from the text object database and provided as the seed of a topic by one of the following two methods:

1. **When there are empty spaces in the conversation-structure space**
   According to subjective experiments in thought-space visualization, people often find new topics in empty spaces of the conversation-structure space [6]. Therefore, when empty spaces exist in the conversation-structure space, a piece of information included in the main empty space is retrieved from the text object database.
   First, a constant number of keywords are obtained by collecting keyword-objects in the order of their distance from the center of the main empty space, and a query keyword set W_q is generated from them. The weight I_{w_i} of each keyword $w_i (w_i \in W_q)$ is calculated by the following equation:

$$I_{w_i} = \frac{min(d_{w_j}; w_j \in W_q)}{d_{w_i}}, \qquad (2)$$

   where d_{w_i} is the distance between the center of the target empty space and the keyword-object w_i. A query keyword vector $\mathbf{Q}$ is generated from the query keywords and their weights.
   The retrieval result is then determined by calculating the inner product of the query keyword vector and each keyword vector of each text object of the text object database. The result is the text object for which the inner product value is the highest. Such a piece of information can be expected to be located in the main empty space and to introduce a new topic.
2. **When there are no empty spaces in the conversation-structure space**
   One way to obtain information about a new topic when there are no empty spaces is to deal with the conversation-structure space in a higher dimension. The conversation-structuring module reduces the original very high dimensional space to a 2-dimensional space. Therefore, even if there are seemingly no empty spaces, there can actually be several empty spaces in a higher dimensional space. However, searching for empty spaces in the original dimensional space requires a very high calculation cost. We therefore use a different method: linear transformation of the system of coordinates based on a specific viewpoint.

In this method, a new topic development direction is obtained by linear transformation of a query keyword vector. The topic-seeds-provision module is equipped with an associative dictionary generated beforehand from a collection of text objects in a certain knowledge domain. The dictionary is constructed as follows [10]. Keywords are extracted from each text object in the same way that keywords are extracted in the utterance-processing module, but all of the keywords are weighted equally. A keyword vector of the text object is generated from the extracted keywords. Then, by using a method based on Associatron [11], one of the associative memory techniques, a self-correlation matrix is calculated from each keyword vector, and an associative memory matrix $\mathbf{M}$ (i.e., the associative dictionary) is obtained by accumulating all of the self-correlation matrices. This associative memory matrix $\mathbf{M}$ thus describes the co-occurring relations between all of the keywords included in the text objects, and it represents the viewpoint that is expressed by the text object set.

This module searches for the main topic cell closest to the newest utterance-object, obtains a constant number of keywords by collecting keyword-objects in the order of their distance from the main topic cell, and generates a query keyword set. The weight of each keyword is calculated in the same way as when empty spaces exist. As a result, a keyword vector $\mathbf{Q}$ is generated, and this vector is linearly transformed by using the associative dictionary; that is the associative memory matrix $\mathbf{M}$:

$$\mathbf{R} = \mathbf{M}\mathbf{Q}, \tag{3}$$

where $\mathbf{Q}$ is a vertical $N \times 1$ vector and we assume that the matrx $\mathbf{M}$ is an $N \times N$ matrix. If the dimensions of matrix $\mathbf{M}$ and vector $\mathbf{Q}$ are different, their dimensions should be adjusted to the larger dimension. Equation (3) is the associative recalling procedure of Associatron. By this linear transformation, the original system of coordinates is transformed into another system of coordinates by distorting, rotating, and shifting the original system, and the original keyword vector is mapped onto the transformed system. Finally, the inner product between the obtained (recalled) vector $\mathbf{R}$ and each keyword vector of each text object in the text object database is evaluated, and the text object that has the highest inner product value is extracted as the retrieval result.

Since the associative matrix $\mathbf{M}$ is constructed from a specific knowledge domain, it can be said that this process is a re-grasping of the meaning of the original topic from the conversationalist's viewpoint. As a result, the conversationalist can introduce a new viewpoint and a new direction. We have already confirmed that the associative method described above has such an effect [10]. Thus, the conversationalist can provide the seed of a new topic even if no empty spaces exist.

5 Experiments

5.1 Process Of The Experiment And Results

We applied the conversationalist to an experimental conversation in which four participants discussed, as the global topic, whether or not a "kangaroo-bar", i.e., a bar equipped on a car which protects the car when the car and a kangaroo come into contact, should be prohibited in Japan. The conversationalist's knowledge (the text object database and the associative dictionary) was generated from articles of "Gendai Yougo no Kiso Chishiki '93 (A Japanese dictionary of contemporary vocabulary in 1993, by Jiyuu Kokuminsha Co.). The number of articles in the article database was 10,406 and the number of keywords in the associative dictionary was 37,502.

Figure 2 shows the conversation situation when 30 utterances have so far been provided by the human participants. The right window shows the utterances with their user-IDs and the left window shows the conversation-structure space. Each icon in the left window corresponds to each utterance in the right window. Figure 3 shows the topic-development structure obtained by the topic-development-recognition module based on the conversation situation of the left window in Figure 2. Cells marked "T" represent main topic locations, and "E" represents the center of an empty space. In Figure 3, we can see that there are three main topics and the right lower empty space is the largest. The main topics are: about car safety equipment (in the upper-left direction), about the relation between a kangaroo-bar and fashion trends (in the downward direction), and about experimental data on the dangers of a kangaroo-bar (in the upper-right direction).

The topic-transition-observation module detected a topic transition at the eleventh utterance. After that, however, no topic transition was detected until the thirtieth utterance after twenty utterances. Thus, the topic-transition observation-module detected a stagnation in the conversation and invoked the topic-seeds-provision module. The topic-seeds-provision module retrieved the text object database by using keywords based on the largest empty space. The piece of information extracted was as follows and the conversationalist provided it as its utterance.:

> *U-curve shape of personal consumption*: According to a survey on consumers of expensive cars in the USA, a U-curve shape consumption tendency (i.e., not only people in the upper income bracket but also people in the lower income bracket tend to spend much money on expensive goods) was observed. The same tendency can be observed in Japan, too. This tendency is caused by the following reason: although people in the middle income bracket tend to spend much money on housing and education for their children, young single people spend all of their income on themselves in spite of their low income. In particular, such a tendency can be observed for people with hobbies, e.g., a car, audio equipment, and leisure activities.

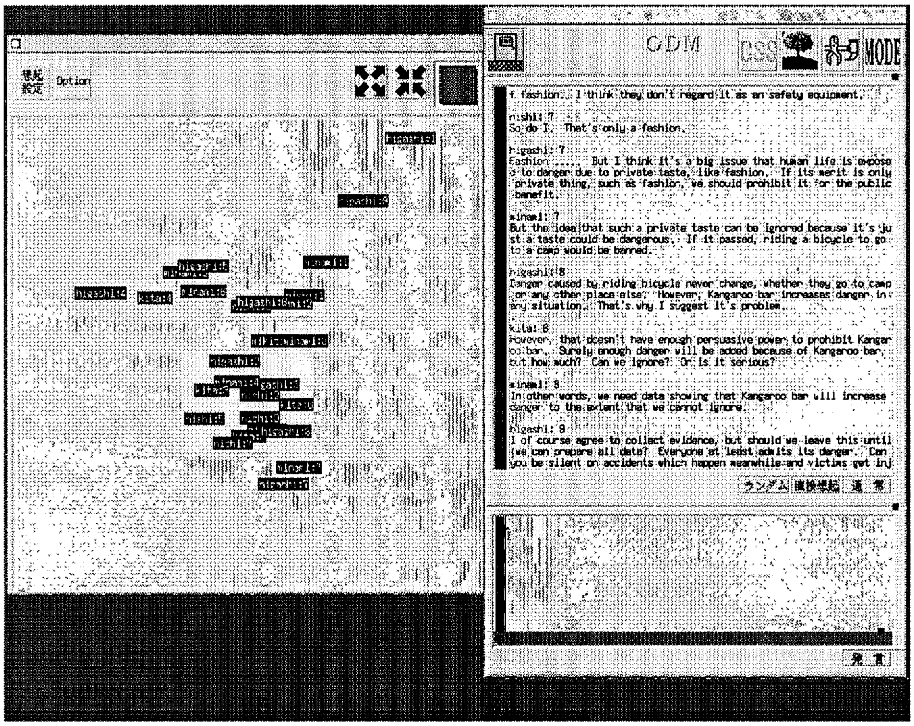

Fig. 2. Conversation situation when 30 utterances had so far been provided by the human participants.

This information was plotted where the largest empty space used to be, by the conversation-structuring module.

5.2 Discussion

The main empty space the conversationalist used for obtaining query keywords was surrounded by topics on experimental data of the dangers of a kangaroo-bar and the relation between a kangaroo-bar and fashion trends. The piece of information (the conversationalist's utterance) was about survey data relating to cars, although it did not relate to a kangaroo-bar. The information mentioned that young single people tend to spend a lot of money on cars as a hobby. The piece of information can therefore be semantically regarded as information in the main empty space.

The kind of consumers who tend to install a kangaroo-bar on their cars had not been referred to in the conversation until the 30th utterance. The piece of information provided by the conversationalist, however, let the participants know that young single people tend to spend unreasonable amounts of money on fashionable things as a hobby, and that there is a high possibility that young

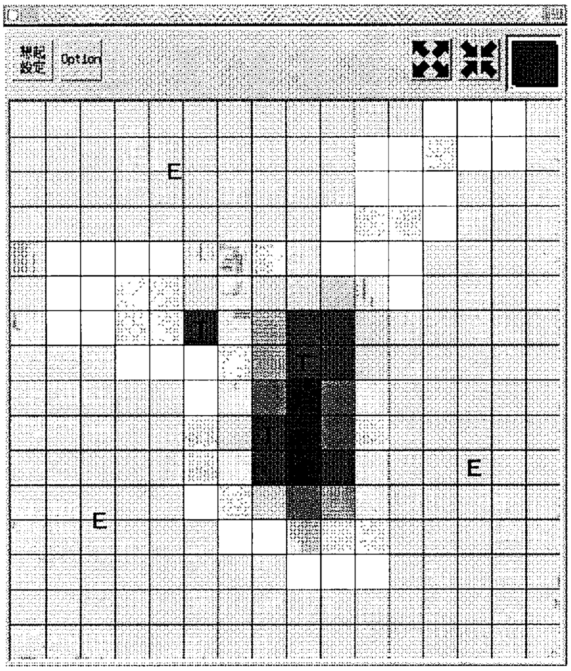

Fig. 3. Topic-development structure based on the conversation situation of the left window of Figure 2.

people would like to install kangaroo-bars on their cars. Consequently, the participants were able to notice that they should consider such a consumption tendency and life-style when thinking about the kangaroo-bar problem. Thus, it can be expected that a conversation will develop in a new direction with the conversationalist.

We asked another subject who did not attend the conversation to read the log file of the conversation. After reading it, the subject gave us the impression that the conversation went in circles before the intervention. That is, although the conversation seemed lively with its many utterances, it was actually in stagnation. Therefore, the conversationalist's intervention was appropriate and timely.

Furthermore, we found that the conversationalist's intervention had mental effects as well as semantic effects. The participants were very excited by their discussion, but when the conversationalist provided a very objective piece of information, the excited conversation tended to calm down. This effect can be expected to help a conversation stay reasonable.

Consequently, we can say that the conversationalist effectively and timely introduced a new topic and a new viewpoint to the conversation as expected. Moreover, the conversationalist's opinion can keep a conversation from becoming emotional and thus help keep it reasonable.

6 Creating Agents With Various Characteristics

The agent's knowledge consists of the associative dictionary that represents the agent's viewpoint and the text-object database that represents the agent's memory. Moreover, the structure of the agent's knowledge is very simple. Therefore, agents with various types of knowledge can be constructed easily by combining various associative dictionaries and text-object databases. In this section, we introduce several examples of such agents and their interesting applications.

The first example is an outsider agent, or an agent who has domain knowledge different from that of the users. People who have the same domain knowledge often share fixed ideas. Therefore, it is often hard to obtain diverse pieces of information outside the frame of the fixed ideas even if they have a brainstorming session. In such a case, experience tells us that it is effective for an outsider who has a different domain knowledge to attend the brainstorming session. We can easily create such an agent by providing an associative dictionary and a text-object database constructed from domain knowledge different from that of the participants in the brainstorming session. We have already confirmed that such an agent can obtain pieces of information which have not only direct relevance but also hidden relevance to an input query text [10].

The second example is an agent that is the agent of a specific person. It can be created by extracting knowledge from a person's writings (e.g., novels or technical/scientific papers). Such an agent provides pieces of information reflecting the person's knowledge. Thus, we can simulate a discussion with the person by talking with the agent not only if the person is simply absent but even if the person died hundreds of years ago. For example, by constructing an agent's knowledge from Shakespeare's writings or Newton's papers, we can virtually talk with them. Additionally, a user can create an agent of himself/herself and give the agent knowledge through his/her writings. By talking with this self-agent, the user can recall what he/she used to think, and, moreover, can find new relevance among pieces of information that he/she knows.

The third example is an agent that has heterogeneous knowledge. There are two methods for obtaining heterogeneous knowledge. One method is to combine an associative dictionary and a text-object database whose knowledge domains are not the same. For example, by combining an associative dictionary generated by Newton's or Shakespeare's writings and a text-object database of contemporary information, it is possible to create an agent with contemporary information but reflecting an ancient person's viewpoints. The other method is to combine plural associative dictionaries of different knowledge domains. This can be done easily by multiplying associative memory matrices. By using such a multiplied associative dictionary, it is possible to obtain new relevance that cannot otherwise be obtained by using each associative dictionary individually. This method can thus be used to create an agent that is a multi-domains expert. Moreover, by multiplying the associative dictionaries of more than one person (for example, the user's own associative dictionary and Newton's associative dictionary) a very interesting viewpoint for the user could be generated.

Thus, various agents characterized by various combinations of various knowledge can be created very easily. By preparing agents with specific knowledge on demand, we can be expected to be able to converse much more creatively.

7 Conclusion

We described a topic-development agent that enters a daily conversation as an equal participant with human participants in order to keep the conversation lively. This agent grasps the relevance of utterances as spatial arrangements, detects a novel direction in which a new topic can be developed, and provides an appropriate piece of information which might likely form the seed of a new topic. In this process, the agent deconstructs and reconstructs conversational topics and contents based on the agent's own viewpoint. Hence, the agent can be regarded as an "emergence agent" in a conversation environment, which is different from the emergence agent of [12] which deconstructs and reconstructs geometrical objects.

From the experimental results, it is suggested that this agent can provide timely information that introduces a new topic. Moreover, it is also suggested that the agent has the ability to refresh the atmosphere of a conversation. Thus, the agent has the ability to effectively coordinate creative aspects of conversations without imposing any of the special restrictions which most ordinary creative discussion systems place on participants. This feature makes it possible to apply the agent to daily conversations that are held in environments characterized as free.

We are planning to apply this agent to various kinds of conversations in order to confirm the effects of conversation activation. Furthermore, we are planning to build agents that have various kinds of characters and to experiment with them.

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