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Toward an outsider agent for supporting a brainstorming session — an information retrieval method from a different viewpoint

Kazushi Nishimoto, Yasuyuki Sumi, Kenji Mase

ATR Media Integration & Communications Research Laboratories, 2-2 Hikari-dai, Seika-cho, Soraku-gun, Kyoto 619-02, Japan

Abstract

Conflicts among different concepts are often useful in creating new ideas. Therefore, an outsider's attendance at a brainstorming session is often effective for activating a brainwave. Our research goal is to construct an artificial outsider agent. As the first step toward the goal, we propose an outsider model as an information retrieval model for obtaining information that has not only evident relevance but also hidden relevance for users. A prototype system has been constructed. Subjective experiments using the prototype system and a detailed analysis of the results confirm that the outsider model can extract such information. Furthermore, we propose a method to combine plural domains of knowledge. It is expected that the combining method can generate new relevance that could not be obtained by using the knowledge domains individually.

Keywords: Divergent thinking; Information retrieval; Outsider agent

1. Introduction

It is said that there are two significant stages in the human creative process: divergent thinking and convergent thinking [1]. In the divergent thinking process, it is important for people to collect pieces of information even if their relevance to the problem is not immediately clear [2]. Then, in the convergent thinking process, if someone can find some new unknown relevance from among the seemingly disparate pieces of information, a new idea can be obtained [3].

Brainstorming is a well-known method for supporting the divergent thinking process in obtaining diverse information [4]. However, a team of experts who have the same knowledge domain often generally share a common frame of fixed ideas; accordingly, little new information can be expected beyond the frame. Therefore, support methods are necessary, and several challenging ones have been attempted. For example, Young provided a metaphor obtained by using a relational database method [5]. Hori constructed a system name AA1 which supports articulation of concepts [6]. Sumi et al. visualized a user's thought space based on a statistics method [7].

Our approach is construction of an artificial outsider agent. Experience tells us that participation of an outsider in a brainstorming session is effective for obtaining diverse information. Such an outsider has domain knowledge different from that of the experts and thinks about the topics from a different viewpoint. Although pieces of information provided by an outsider can be out of focus or irrelevant, they have relevance from the outsider's viewpoint. Such hidden relevance can stimulate the experts' thinking.

The artificial outsider agent participates in a brainstorming session, listens to the experts' opinions and provides several pieces of information based on the outsider's viewpoint. The goal is illustrated in Fig. 1. As the first step toward this goal, we have been researching a diverse-information extraction method that acts as if it were a human outsider. Ordinary information retrieval methods have mainly focused on obtaining information highly relevant to the query, and therefore have not been able to break the frame of common fixed ideas. This has led to an outsider model that extracts diverse information and a prototype system based on the model [8,9].

In Section 2, we explain the outsider model and the structure of the prototype system. In Section 3, the experiments and the results are presented in order to discuss the basic characteristics of the outsider model. In Section 4, we discuss the expected effects of combining

Email: {knishi,sumi,mase}@mic.atr.co.jp

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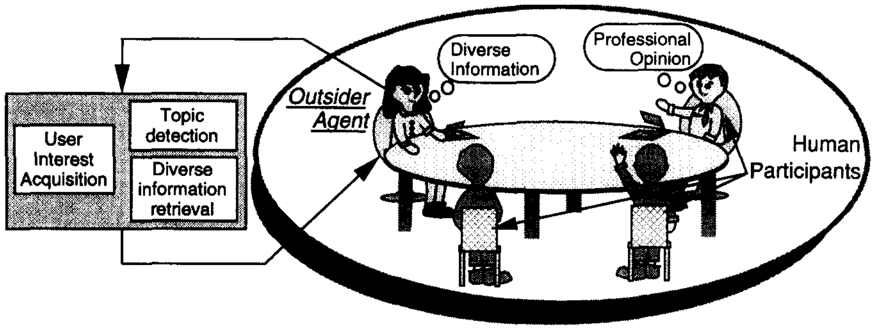

Fig. 1. Goal of artificial outsider agent.

plural knowledge domains and propose a simple combining method. In Section 5, we summarize the characteristics of the outsider model's information retrieval and advantages of an artificial outsider agent.

2. The outsider model and the prototype system

2.1. Effective stimulation of divergent thinking

In this section, we discuss what kind of information can effectively stimulate human divergent thinking.

Fig. 2 shows how the whole information space is classified when a subject of thinking T is given to a person P.

- **Region 1:** Upon receiving the subject T, person P has already recalled information in this region. Boundary a is person P's recognition limit of relevance when subject T was given.
- **Region 2:** Given only subject T, person P has not yet recalled information in this region. However, upon receiving a piece of information in this region, person P can recognize the relevance of the piece. The outer boundary s is person P's subjective recognition limit of relevance.
- **Region 3:** Pieces of information in this region actually have some relevance to subject T. However, person P cannot clearly recognize it even if the pieces of information are given. The outer boundary o is the objective limit of relevance.
- **Region 4:** Pieces of information in this region are completely irrelevant to subject T.

The information in region 2 shows relevance that is known to person P but was overlooked. Therefore, it is expected that such information can be effective in directly breaking person P's fixed ideas. Relevance of the information in region 3 is difficult for person P to clearly notice even if it is given. However, such information actually has some relevance. Therefore, by deeply thinking, studying and finally finding the relevance, it is expected that this information can also be effective in breaking person P's fixed ideas.

On the other hand, the completely irrelevant information in region 4 cannot be expected to affect human thinking effectively. Information in region 1 is basic to thinking about subject T. However, it is already within the scope of person P's thinking. Therefore, it is also unrealistic to expect this information to break the frame of person P's fixed ideas.

Consequently, we can conclude that person P's frame of fixed ideas can be represented by the boundary a or s and that providing information in regions 2 and 3 is an

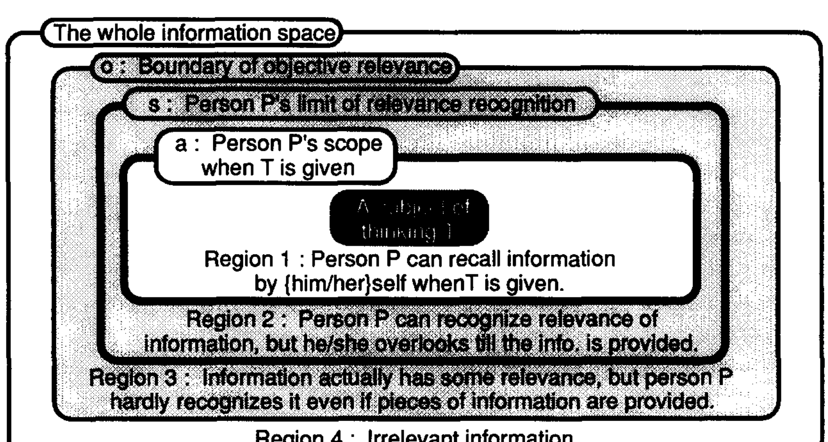

Fig. 2. Classification of the whole information space when a subject of thinking T is given to a person P.

effective method to break the frame. Information included in these regions may be seemingly irrelevant. However, it actually has some hidden relevance. Therefore, such information is essentially different from the information in region 4.

2.2. The outsider model

The outsider model is an information retrieval model for extracting information that has some hidden relevance. This model follows the following three steps.

(a) Coarse grasping of the meaning

The meaning of a participant's opinion is superficially grasped in this step. This process is realized as follows. A set of keywords $G_o = \{g_1, g_2, \ldots, g_i, \ldots, g_{m_g}\}$ is extracted from an opinion O, where g_i is one of the extracted keywords and m_g is the number of extracted keywords. We call this set G_o the "original meaning set". Here, it is assumed that the set G_o can represent the coarse meaning of the opinion, although they do not form sentences.

(b) Shallow understanding

An outsider tries to understand the opinion of other participants by using the outsider's own knowledge domain, which is different from that of the others. This can be regarded as re-expressing the original meaning by using different domain knowledge. This process is realized as follows. First, we prepare an associative dictionary D in the outsider's knowledge domain that is different from the other participants' knowledge domain. By referring to the associative dictionary D, associative word sets are obtained from individual keywords of the original meaning set G_o. All of the associative word sets are examined, and a "re-expressed meaning set G_r" is obtained by extracting words commonly appearing in many of the associative word sets. Consequently, the original meaning set G_o is translated to the re-expressed meaning set G_r. The relevance derived from the outsider's knowledge domain is unexpected by the participants.

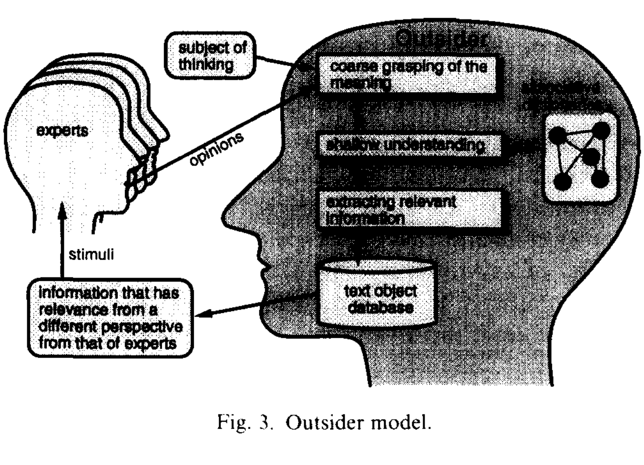

Fig. 3. Outsider model.

(c) Extracting relevant information

Based on the results of understanding in the previous step, the outsider retrieves pieces of information from the outsider's own knowledge. This process is realized as follows. The degree of relevance between the re-expressed meaning set G_r and each text object in a text object database is calculated, and several text objects that have a high degree of relevance are extracted.

Fig. 3 shows the outsider model.

2.3. Structure of the prototype system

Fig. 4 shows the software structure and process flow of a prototype system based on the outsider model. The system has two process phases: knowledge building phase and information retrieval phase.

In the knowledge building phase, we first prepare a set of text objects in the knowledge domain that the system should have. Each text object is input into the parser. After the parser analyzes a text object, it generates a text object vector for the text object. The text object vector is input into the associative memory module and the module generates/renews the associative dictionary D. On the other hand, the database manager registers each text object together with its text object vector to a text object database. As a result, the system knowledge (i.e. the associative dictionary and the text object database) that depends on the knowledge domain of the prepared set of text objects is constructed.

In the information retrieval phase, an input into the system is an opinion of a participant. The parser analyzes the opinion and generates an opinion vector. This vector corresponds to the original meaning set G_o. Using the opinion vector and the associative dictionary D, the associative memory module recalls a certain keyword vector. This recalled vector corresponds to the re-expressed meaning set G_r. The database manager calculates the degree of resemblance between the recalled vector and

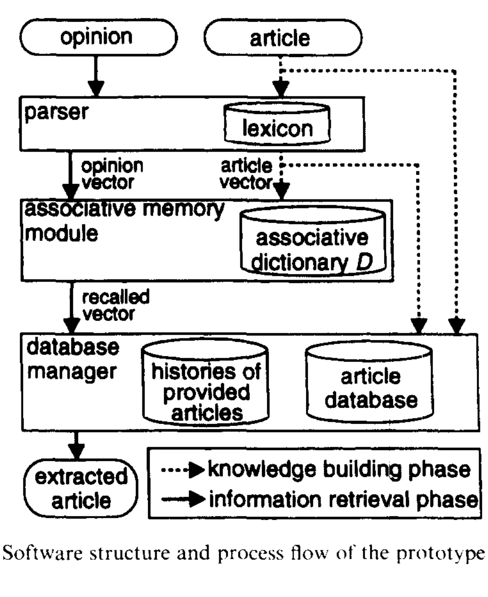

Fig. 4. Software structure and process flow of the prototype system.

the text object vector of each text object stored in the text object database. Consequently, a text object with a high degree of resemblance is provided as the output of the system.

The details of each module are explained below.

(a) Parser

This module morphologically analyzes the input text (i.e. a text object or an opinion) and extracts nouns and unknown-part-of-speech-words as keywords by the order in the text. Even if a word repeatedly appears in a text, the word is employed as a keyword only once. A keyword vector (i.e. a text object vector or an opinion vector) is then generated as follows.

In the knowledge building phase, where n is the number of text objects to be memorized, a text object vector $\mathbf{K}_j$ of a text object $A_j (j = 1 \sim n)$ is denoted by the following notation:

$$\mathbf{K}_j = (\delta_1, \delta_2, \ldots, \delta_i, \ldots, \delta_{m_T})^{\mathrm{t}}; \delta_{\mathrm{i}} = \begin{cases} 1; & w_i \in A_j \\ 0; & w_i \notin A_j \end{cases}, \tag{1}$$

where m_T is the total number of keywords obtained from n text objects (even if a certain keyword is included in plural text objects, it is counted only once). w_i is the i-th keyword of the total keyword set $W_T = \{w_i; 1 \leq i \leq m_T\}$. Therefore, the keyword w_i that corresponds to δ_i, whose value is 1, is considered one of the keywords from the text object A_j. "$\mathbf{X}^{\mathrm{t}}$" denotes the transposition of a vector $\mathbf{X}$.

In the information retrieval phase, using an opinion keyword set $W_o = \{q_1, q_2, q_3, \ldots, q_k, \ldots\}$ obtained from an input opinion O, an opinion vector $\mathbf{Q}$ is generated as follows.

$$\mathbf{Q} = (\delta_1, \delta_2, \ldots, \delta_i, \ldots, \delta_{m_T})^{\mathrm{t}};$$

$$\delta_i = \begin{cases} 1; & \exists w_i = q_k; w_i \in W_T \\ 0; & \text{otherwise} \end{cases} \tag{2}$$

This vector corresponds to the original meaning set G_o.

The number of δ_i, whose value is 1 in both the text object vectors and the opinion vectors, is restricted to under m_u (constant).

(b) Associative memory module

Associatron [10] was applied to the associative memory method. From this, in the knowledge building phase, n text object vectors are memorized as follows:

$$\mathbf{M} = \sum_{j=1}^{n} \mathbf{K}_j \mathbf{K}_j^{\mathrm{t}}, \tag{3}$$

where $\mathbf{M}$ is an associative memory matrix describing co-occurrent relations between individual keywords and corresponds to the associative dictionary D.

In the information retrieval phase, recalling is done from the opinion vector $\mathbf{Q}$ by using the associative memory matrix $\mathbf{M}$ as follows:

$$\mathbf{R} = \phi_\theta(\phi_{\theta=0}(\mathbf{M})\mathbf{Q}), \tag{4}$$

where $\mathbf{R}$ is a recalled vector and corresponds to the re-expressed meaning set G_r. ϕ_θ is the quantizing operator that quantizes each element, i.e. x_{ij} of a matrix $\mathbf{X}$, by a threshold θ. In other words, the operation $\mathbf{X}' = \phi_\theta(\mathbf{X})$ is defined as the following equation:

$$x'_{ij} = \begin{cases} 1; & x_{ij} > \theta \\ 0; & 0 \leq x_{ij} \leq \theta \end{cases} \tag{5}$$

The value of θ of the outer ϕ_θ in Eq. (4) is determined to restrict the number of elements, whose value is 1 in the recalled vector $\mathbf{R}$, to less than m_u for every recalling.

(c) Database manager module

In the knowledge building phase, this module registers each input text object A_j along with its text object vector $\mathbf{K}_j$ to a text object database.

In the information retrieval phase, this module calculates the degree of resemblance r_j between the recalled vector $\mathbf{R}$ and each text object vector $\mathbf{K}_j (j = 1 \sim n)$ as follows:

$$r_j = \frac{\mathbf{K}_j^{\mathrm{t}} \cdot \mathbf{R}^{\mathrm{t}}}{\sum_{\delta_i \in \mathbf{R}} \delta_i} \times \frac{\mathbf{K}_j^{\mathrm{t}} \cdot \mathbf{R}^{\mathrm{t}}}{\sum_{\delta_i \in \mathbf{K}_j} \delta_i}, \tag{6}$$

where "$\mathbf{X} \cdot \mathbf{Y}$" denotes the inner product of the vectors $\mathbf{X}$ and $\mathbf{Y}$.

This module also has a history containing the list of text objects already extracted as outputs. By referring to it, the system can always provide a new text object to participants and avoid providing already presented text objects.

3. Basic characteristics analysis

3.1. Subjective experiments and the results

We conducted subjective experiments to confirm the basic characteristics of the outsider model. The employed subjects were members of our laboratory. Therefore, they could be regarded as "same-domain" experts at least in computer science. The number of subjects was 24. The knowledge of the prototype system was generated from articles of "Gendaiyougo no Kisochishiki 93" (A japanese dictionary of contemporary vocabularies in 1993) by Jiyuu Kokumin Sha Co. The number of memorized articles was 10 406, and the total number of keywords m_T was 37 502.

We prepared three experimental systems with the following algorithms:

(1) Outsider algorithm: This is the prototype system described in Section 2.

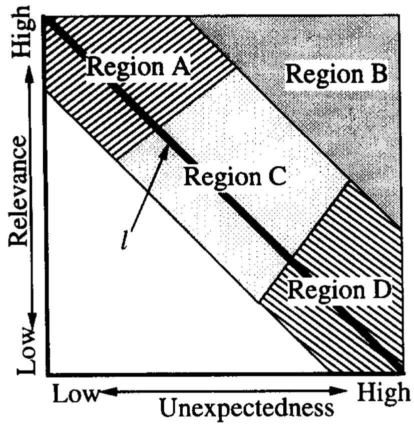

Fig. 5. Four regions of the plotted evaluation results.

(2) Direct algorithm (Conventional retrieval algorithm): The prototype system without the shallow understanding step (the associative memory module) is equivalent to this. Namely, an opinion keywords set W_0 is directly used to retrieve the text object database.
(3) Random algorithm: Text objects are randomly extracted from the text object database.

By comparing text objects extracted by algorithm (1) with the other two algorithms, we could confirm the basic characteristics of the outsider model.

We used the introduction part of an engineering paper as an opinion. This paper discusses the virtual reality teleconference system that has been researched at our institute. Therefore, all of the subjects were quite knowledgeable about the contents. Five text objects for each algorithm were extracted. The input opinion and a total of fifteen extracted text objects were given to the subjects by concealing the algorithms that extracted the text objects.

We conducted two subjective experiments. In the first experiment, the subjects were instructed to compare the opinion and each text object quickly, and then perform evaluations from the following two viewpoints:

(a) Relevance: to what degree were the input opinion and the extracted text object relevant? [0: No relevance, 10: Very strongly relevance]
(b) Unexpectedness: To what degree were not you able to predict that such a text object was provided from the opinion? [0: Able to easily predict, 10: Completely unable to predict]

Evaluation results are plotted in the graph shown in Fig. 5.

After the first experiment, we related the following condition to the subjects and conducted the second experiment.

"You are discussing the teleconference system with your colleagues and an outsider. One of your colleagues states the input opinion as a personal opinion and after that the outsider gives articles as relevant opinions to your colleague's opinion. By considering this situation, to what degree were the opinion and the text objects relevant? [0: No relevance, 10: Very strong relevance] Think deeply, if needed."

Figs. 6, 7, 8 and Table 1 show the evaluation results. Fig. 6 shows scatter diagrams of the evaluation results of all text objects by all of the subjects for the three algorithms after a quick initial evaluation in the first experiment. Fig. 7 shows the profile of the scatter diagrams along each axis. It also shows the average frequency of the direct algorithm and the random algorithm. Fig. 8 shows how many text objects increased the degree of relevance by more than one after deep thinking in the second experiment. Table 1 shows the total increase in the degree of relevance between the first experiment and the second one for each algorithm. The total relevance increase of an algorithm α (TRI_α) is calculated by the following equation:

$$TRI_\alpha = \sum_i \sum_j (D_{ij} - R_{ij}) \tag{7}$$

where D_{ij} is the relevance degree obtained in the second experiment (deep thinking) for text object j by subject i, and R_{ij} is the relevance degree obtained in the first

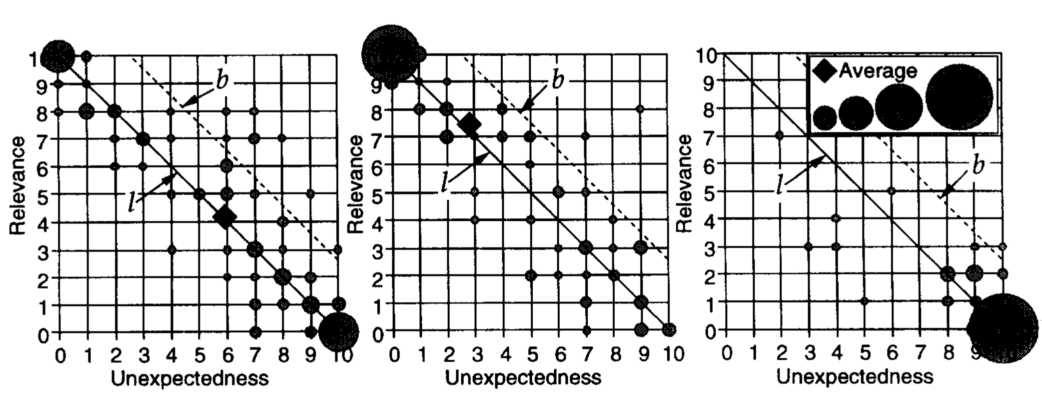

Fig. 6. Scatter diagrams of evaluation results of all text objects by all subjects. The size of circles expresses number of text objects. (a) Outsider algorithm; (b) direct algorithm; (c) random algorithm.

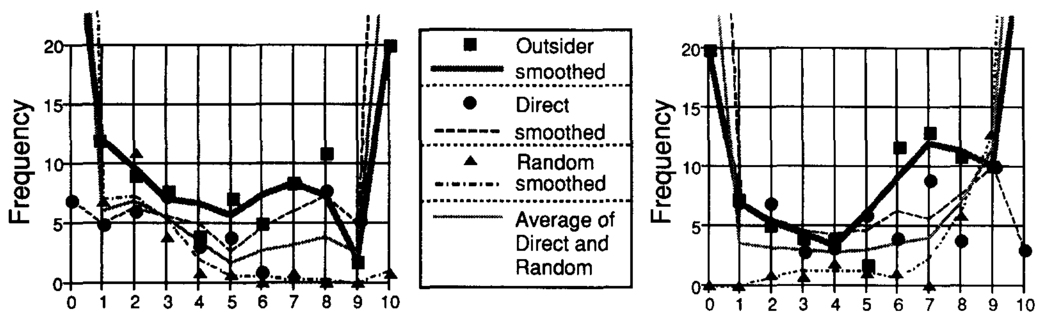

Fig. 7. Histograms of frequency at each degree of relevance (left) and unexpectedness (right).

experiment (quick evaluation) for text object j by subject i.

3.2. Discussion

3.2.1. Evaluation policy

As discussed in Section 2.1, it is necessary to extract information in regions 2 and 3 of Fig. 2 in order to stimulate human divergent thinking and to support human creativity.

Generally speaking, it is difficult to clearly notice hidden relevance, which is felt vaguely. Therefore, most of the text objects that have hidden relevance to the opinion are evaluated as moderately relevant as well as moderately unexpected. Thus, region C of Fig. 5 corresponds to region 3 of Fig. 2. If such hidden relevance of a text object is noticed as soon as a text object is provided, the text object is evaluated as not only highly relevant but also as highly unexpected and is plotted in the far-upper-right region of line l of Fig. 5, which is denoted as (Relevance + Unexpectedness) = 10. Thus, region B of Fig. 5 corresponds to region 2 of Fig. 2.

On the other hand, text objects whose relevance people already know are evaluated as high relevance and low unexpectedness. Therefore, region A of Fig. 5 corresponds to region 1 of Fig. 2. Entirely irrelevant text objects are evaluated as low relevance and high unexpectedness. Therefore, region D of Fig. 5 corresponds to region 4 of Fig. 2.

Consequently, we can conclude that an algorithm that extracts many text objects in regions B and C of Fig. 5 is needed.

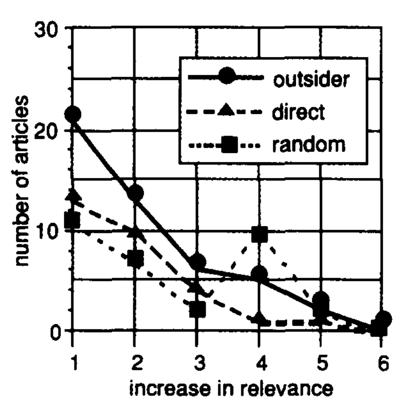

Fig. 8. Number of articles whose relevance increased by more than one after deep thinking.

3.2.2. Basic characteristics of the outsider model

Based on the experimental results and the evaluation policy, we will now discuss the basic characteristics of the outsider model.

(A) Ability to obtain information with moderate relevance and moderate unexpectedness. By looking at the average value in Fig. 6, the following overall characteristics of each algorithm are easily recognized:

- The direct algorithm extracts information with high relevance and low unexpectedness.
- The random algorithm extracts information with very low relevance and very high unexpectedness.
- The outsider algorithm extracts information with moderate relevance and moderate unexpectedness.

The difference in relevance and unexpectedness between the direct algorithm and the outsider algorithm and that between the random algorithm and the outsider algorithm were significant by t-test.

The distribution of evaluation results in Fig. 6(1) seems to be obtained by the simple combination of the other two algorithms. However, Fig. 7 shows that the outsider algorithm obtained more pieces of information in the moderate relevance and moderate unexpectedness region (from 2 to 8 degrees) than both of the other two algorithms as well as their average.

Consequently, information with moderate relevance and moderate unexpectednesss can effectively be obtained by the outsider algorithm.

Table 1
Total increase in relevance degree after deep thinking.

Algorithm	Outsider	Direct	Random
TRI_0	107	54	81

(*B*) *Ability to obtain information with high relevance and high unexpectedness.* It has conventionally been expected that most of the results will scatter near line l in Fig. 6. However, as we discussed in Section 3.2.1, it has also been expected that some results scatter in the high relevance and high unexpectedness area, i.e. the far-upper-right region of line l. The distance between line l and line b is $\bar{d} + 2\sigma$, where $\bar{d}$ is the average of distances between line l and all of the evaluation results and σ is the standard deviation. In the upper-right region of line b, there are eight points in Fig. 6(1), two points in Fig. 6(2) and only one point in Fig. 6(3). It is statistically expected that there would be 2.2% the amount of data, say two or three points on average in each diagram if we assume a normal distribution and there are two or three times as many points in Fig. 6(1). It is difficult to make a clear conclusion with only a small amount of data. However, the results suggest that the outsider model can obtain better highly relevant and highly unexpected information than the other algorithms.

(*C*) *Ability to obtain information which have hidden relevance.* In Fig. 8, the increase in the relevance degree after deep thinking by the outsider algorithm is larger than that of the others at most of the points. The outsider algorithm achieved the best results for total relevance increase TRI_α, as shown in Table 1. The random algorithm has the largest margin of relevance. Therefore, the random algorithm is potentially able to achieve the largest increase. However, the outsider algorithm had the largest increase. The increase in relevance is derived from finding the hidden relevance. Consequently, the results support our conclusion that information obtained by the outsider algorithm has more hidden relevance than information obtained by the other algorithms.

The shallow understanding step of the outsider model takes its relevance from a different viewpoint of the original opinion. Text objects are retrieved not only by keywords originally included in the input opinion but also by associated words. Therefore, the text objects include not only direct relevance to the opinion but also different relevance. Such different relevance can be considered hidden relevance. Although it is difficult for many of the subjects to clearly recognize the hidden relevance at first, some of the subjects do notice it after deep thinking.

Since the knowledge domain of the text objects is different from the subjects' knowledge domain, it may seem very natural that diverse information is obtained. However, the experimental results show that information obtained with the direct algorithm was not diverse in spite of using the text objects set of the different knowledge domain. This fact indicates that only preparing a text object set of the different knowledge domain is not sufficient. In order to exploit the difference of the text object set, it is essential to prepare a kind of bird's-eye-view information of the set. In the outsider model, the associative dictionary plays the role of bird's-eye-view information.

4. Discussion of multi-domain knowledge

The artificial outsider agent has many advantages over a human outsider. One of the important advantages is that the artificial outsider agent can easily have plural knowledge domains. Furthermore, the fusion of plural domains can obtain novel relevance that could not be obtained by individually dealing with each knowledge domain. This section mentions briefly how this is possible.

Let's start by combining two domains of knowledge, i.e. K_a and K_b. By using text object sets of K_a and of K_b, associative dictionaries $\mathbf{M}_a$ and $\mathbf{M}_b$ are generated, respectively, in the same manner described in Section 2.3. Here, we assume that the word order is arranged so that the i-th word of K_a and K_b are identical and the dimensions of $\mathbf{M}_a$ and $\mathbf{M}_b$ are same.

Multiplying the associative dictionaries $\mathbf{M}_a$ and $\mathbf{M}_b$ is a simple way to do this. In this method, recalled vector $\mathbf{R}$ is calculated by the following equation:

$$\mathbf{R} = \phi_\theta\{\phi_{\theta=0}(\mathbf{M}_a\mathbf{M}_b)\mathbf{Q}\} \oplus \phi_\theta\{\phi_{\theta=0}(\mathbf{M}_b\mathbf{M}_a)\mathbf{Q}\}, \qquad (8)$$

where operator "$\oplus$" denotes a logical-OR of each element of two vectors.

Fig. 9 shows how new relevance is obtained by this operation. In this very simple example, associative dictionaries $\mathbf{M}_a$ and $\mathbf{M}_b$ of knowledge domains K_a and K_b are constructed by co-occurrence relations among three words w_1, w_2 and w_3. Here, we assume that $\mathbf{M}_a$ includes as co-occurrence relation only between w_1 and w_3, and that $\mathbf{M}_b$ includes a co-occurrence relation only between w_1 and w_2, except for the co-occurrence relation of each word itself. Namely, there are no relations between w_2 and w_3 in $\mathbf{M}_a$ and $\mathbf{M}_b$. Therefore, in the case of a query sentence consisting of only word w_2, w_3 is never recalled from the query sentence by using either $\mathbf{M}_a$ or $\mathbf{M}_b$ individually (see the results of $\mathbf{M}_a\mathbf{Q}$ and $\mathbf{M}_b\mathbf{Q}$). However, by multiplying $\mathbf{M}_a$ and $\mathbf{M}_b$, a relation

$$\mathbf{Q} = (0 \quad 1 \quad 0)^t$$

$$\mathbf{M}_a = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix} \mathbf{M}_b = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

then

$$\mathbf{M}_a\mathbf{Q} = (0 \quad 1 \quad 0)^t$$

$$\mathbf{M}_b\mathbf{Q} = (1 \quad 1 \quad 0)^t$$

$$\mathbf{M}_a\mathbf{M}_b\mathbf{Q} = (1 \quad 1 \quad 1)^t$$

Fig. 9. Simple example of effect of multiplying associative dictionaries.

between w_3 and w_2 is generated by using w_1 as a mediator. As a result, w_3 can be recalled by the query sentence (see the results of $\mathbf{M}_a\mathbf{M}_b\mathbf{Q}$). Thus, a new relation between w_2 and w_3 can be obtained by multiplying two different knowledge domains, i.e. K_a and K_b.

Consequently, we can say that a new domain of knowledge (in other words, new bird's-eye-view information) is generated by multiplying different knowledge domains, i.e. different associative dictionaries. Therefore, if we simply prepare n knowledge domains, we can obtain $\Sigma_{i=1}^{n} nC_i$ knowledge domains equivalent. Furthermore, combining plural knowledge domains can be achieved very easily as described above. It is hard to obtain such a feature with real persons even if they have different knowledge domain individually. This is a very important feature of the artificial outsider agent. We will confirm this feature in the near future.

5. Conclusion

As the first step to create an outsider agent for supporting the human divergent thinking process, especially for supporting a brainstorming session, we proposed an outsider model and constructed a prototype system for obtaining information from a different viewpoint. Using the prototype information retrieval system, we conducted subjective experiments to evaluate the system's basic characteristics. Comparing the prototype system based on the outsider algorithm with the direct algorithm and the random algorithm, we obtained the following results:

(a) Moderately relevant and moderately unexpected information can be obtained with the outsider algorithm.
(b) There is a high possibility of extracting highly relevant as well as highly unexpected information with the outsider algorithm.
(c) The outsider algorithm has a high capability to obtain information with hidden relevance. Such information cannot be obtained by only using a database in a different knowledge domain from that of the users. In order to use the difference in knowledge domain effectively, bird's-eye-view information of the database is needed. In the prototype system, the associative dictionary plays this role.

Furthermore, we showed the possibility of a new knowledge domain being generated by a combination of different knowledge domains. Such combination provides new relevance that cannot be obtained from each knowledge domain individually. Moreover, we proposed a simple method to combine plural knowledge domains.

The structure of knowledge in our artificial outsider agent is very simple compared with conventional AI systems, in particular expert systems. However, this feature provides strong advantages of the artificial outsider agent. First, it is very easy to let the outsider agent have any necessary knowledge domain and any combination of plural knowledge domains. Second, the outsider agent has robustness in its adaptability to any domain of brainstorming.

We believe that innocent thinking, including simple and shallow knowledge, plays a vital role in stimulating creativity, in addition to the traditional view that complex thinking, such as expert reasoning and well-structured knowledge, is essential in the process. The role that innocent thinking plays is analogous to the way children often give us marvelous ideas.

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