

PAPER

Analysis of The Similarity of Individual Knowledge and The Comprehension of Partner's Representation during Collaborative Concept Mapping with Reciprocal Kit Build Approach

Lia SADITA^{†a)}, Pedro Gabriel Fonteles FURTADO[†], Nonmembers, Tsukasa HIRASHIMA[†], and Yusuke HAYASHI[†], Members

SUMMARY Concept mapping is one of the instructional strategies implemented in collaborative learning to support discourse and learning. While prior studies have established its positive significance on the learning achievements and attitudes of students, they have also discovered that it can lead to students conducting less discussion on conceptual knowledge compared to procedural and team coordination. For instance, some inaccurate ideas are never challenged and can become ingrained. Designing a learning environment where individual knowledge is acknowledged and developed constructively is necessary to achieve similarity of individual knowledge after collaboration. This study applies the Reciprocal Kit Build (RKB) approach before collaborative concept mapping. The approach consists of three main phases: (1) individual map construction; (2) re-constructural map building; and (3) difference map discussion. Finally, each team will build a group map. Previous studies have shown that the visualization of similarities and differences during the third phase correlates with the improvement of concept map quality. The current paper presents our investigation on the effects of the first and second phases in terms of the final group products. We analyze the correlations between the similarity of individual knowledge represented in the first-phase maps, the comprehension of partner's representation during the second phase, and the changes of map scores. Our findings indicate that comprehension level is a stronger predictor than the similarity of individual knowledge for estimating score gain. The ways in which patterns of knowledge transfer from individual to group maps, which exhibit how the group products are built based on individual inputs, are also discussed. We illustrate that the number of shared and unshared links in the group solutions are proportionally distributed, and that the number of reconstructed links dominates the group solutions, rather than the non-reconstructed ones.

key words: collaborative concept map, kit-build, collaborative learning, boundary crossing

1. Introduction

Mutual understanding of the partner's perspectives and shared interpretations of the problem being addressed are essential requirements for collaboration. Heterogeneous group composition promotes the negotiation of perspectives towards a shared understanding. However, in a practical classroom situation, assessing similarities of prior knowledge beforehand is not always applicable. Previous studies suggest that social interaction is essential for promoting knowledge convergence; i.e., an increase in knowledge pos-

essed by all collaborating partners after collaboration [1]–[3]. Some researchers have attempted to promote productive interaction by employing script, scenario, or visualization tools [4], [5].

Concept maps have been extensively used as a visualization tool to articulate complex ideas and maintain shared focus during a discussion. Studies have found that employing a concept map in collaborative learning shows significant learning gains related to the quality of student interaction during discussions [5], [6]. Moreover, collaborative concept mapping activity has a positive effect on students' attitudes, specifically in increasing group motivation and students' responsibility for their own learning [5], [7]. However, conflicting evidence has also been found, indicating that students spend a considerable amount of time focusing on task collaboration, procedure coordination, and team coordination, rather than on discussions about the concepts or relationships involved [8]. Others have also found that some inaccurate ideas are never challenged and can become ingrained [9].

A strategy to foster knowledge convergence during collaboration is by nurturing group members to apply the knowledge available to them, both shared and unshared knowledge. The current study employs the Reciprocal Kit Build (RKB) approach, as introduced by [10], [11], to allow students to externalize their thinking, exchange knowledge through reconstruction, and discuss group members' similar and dissimilar areas of understanding, with the support of a difference map. The approach engages group members to operate on boundary objects; i.e., the map structures and components. Through utilizing these boundary objects, various learning mechanisms, such as coordination, reflection, and transformation of individual knowledge, are expected to occur.

Previous studies showed that the RKB approach promotes productive discussion [10], [11]. Unlike those studies, after following the proposed activity, we ask the students to build an integrated map that represents their understanding as a group. A preliminary study on RKB for collaborative learning has explained how the approach affects collaborative learning outcomes and students' learning experiences [12]; however, it does not investigate how individual prior knowledge convergence and comprehension levels through reconstruction may potentially influence the final

Manuscript received November 18, 2019.

Manuscript revised March 11, 2020.

Manuscript publicized April 10, 2020.

[†]The authors are with the Dept. of Information Engineering, Hiroshima University, HigashiHiroshima-shi, 739–8511 Japan.

a) E-mail: lia@lel.hiroshima-u.ac.jp

DOI: 10.1587/transinf.2019EDP7305

collaborative product. It also does not identify how knowledge is potentially transferred from individual solutions, according to the similarity of knowledge and comprehension levels between the group members. Thus, the current study aims to address those issues. Identifying the relationship between the individual and group product is important since there is interdependence between these two. The results of this study highlight the role of individual phases of RKB activities in foreseeing students' learning achievements as a group. The study is implemented in a practical Linear Algebra classroom at a public university in Indonesia.

The structure of this paper is as follows. In Sect. 1, the motivations behind the research are explained, and relevant prior researches are discussed in Sect. 2. Section 3 describes the context and participants of this study, as well as defining the sources of data collection and the metrics used to determine the similarity of students' prior knowledge, the comprehension of group partner representation, transfer of elements from individual to group maps, and the group learning achievements. The results of this study are discussed in Sect. 4, while a summary of the results, findings, and limitations of this study is presented in Sect. 5. The conclusions drawn from this research and some potential future works are available in Sect. 6.

2. Literature Review

2.1 Collaborative Concept Map

The mental models and schemata that are used by cognitive and educational researchers to explain the complex phenomenon of human learning, reasoning, and problem solving are not directly observable [13], [14]. Researchers thus require adequate tools, instruments, and methodologies to assist learners to externalize those knowledge structures [13]. A concept map is a kind of externalization tool that can be manipulated to promote the sophistication of internal knowledge representation (learning). The term "concept map" was first introduced by Joseph D. Novak [15] as a graphical structure that represents one's cognitive knowledge, consisting of concepts and links. A concept map can portray the builder's understanding of the domain depicted in the map [16].

In a collaborative learning context, concept maps may act as a shared representation to support the co-construction of knowledge and maintain shared focus during a discussion. Employing a concept map can also reduce the ambiguity of discussions. Research suggests that the use of concept maps supports all collaborative learning processes; i.e., externalization and elicitation of task-relevant knowledge, and conflict- and integration-oriented consensus building [3], [4]. Nevertheless, studies on various collaborative concept mapping activities have also indicated that this tool can induce more effective discussion; for example, by adding to the individual preparation stage or increasing awareness of group members' knowledge before collaboration. Creating a design of concept map in their own private

spaces can provide students with time to reflect upon, organize, and develop their understanding, potentially leading to more effective expression of individual ideas during a discussion [6], [17]. Increasing group knowledge awareness by showing the partner's concept map and providing access to correlated resources improves the efficiency of knowledge co-construction because students do not need to collect information, but are instead, able to start the problem-solving process directly [18].

2.2 Kit-Build Concept Map

When requested to build a concept map, students are equipped with instructions and conditions, which are referred to respectively as task demands and task constraints: they outline what the student must do to complete the task, and limitations that they must abide by while solving the task [16]. The pre-defined conditions and specifications vary in terms of the structure or the content of the map—from complete freedom of content and/or structure, to restricted content and/or structure. To determine the appropriate building style, the teacher must reflect on the intended purpose of the exercise, as different conditions can affect the quality of the constructed maps [16]. Moreover, assessment of concept maps is highly dependent on the way the maps are created and the purpose of assessment [16]; therefore, the automation of such assessment is challenging.

Kit-Build (KB) is a re-constructural approach of concept mapping, wherein students are requested to build a map based on pre-defined concepts (as nodes) and linking words [19], [20]. These map components are decomposed from an concept map built by an expert; for example, the classroom teacher. Once the map contents are given, the students need to find the most suitable structure for them. This type of concept-map building may not be sufficient to express an individual's knowledge structure regarding a particular topic, but it can allow for prompt evaluation of learners' comprehension of information delivered by the teacher [20].

By employing the KB approach, it is feasible to achieve automatic assessment of concept maps. After students have constructed their maps, the KB analyzer will perform proposition-based similarity matching and display the results to the teacher. The teacher can evaluate students' performance at an individual and a group level. The KB analyzer shows all the same propositions between teacher and students as matching links, propositions created by the teacher but not the students as lacking links, and the propositions constructed only by students as excessive links. Providing map components can help learners to initiate the task, whereas when learners are faced with a blank canvas, they are often intimidated and have difficulty in constructing a map [16]. From the viewpoint of the teacher, understanding and misconceptions by learners can be detected immediately [21]. When the teacher provides feedback to learners, the source of any errors can be traced, and misconceptions can be corrected. Automatic assessment through the KB approach can attain almost the same level of validity as

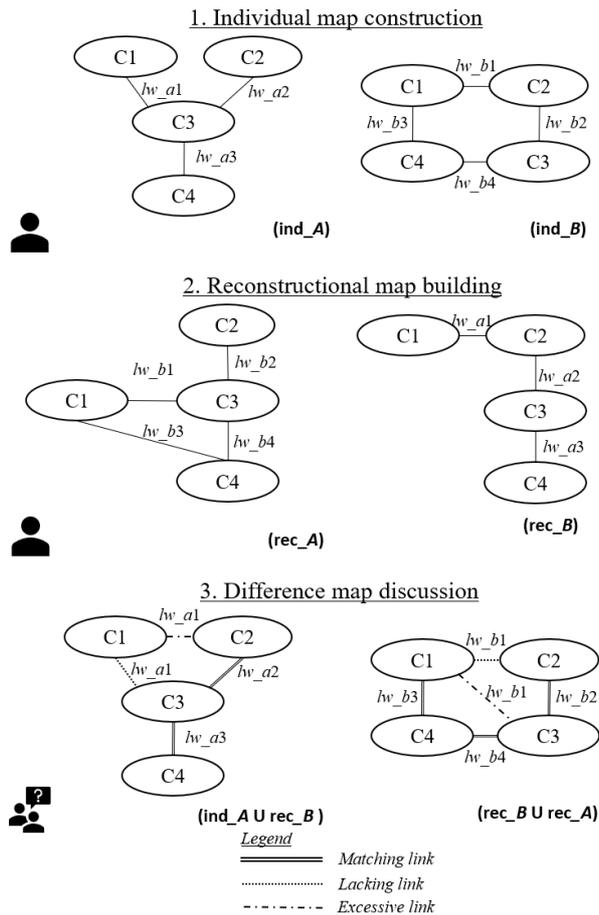


Fig. 1 Illustration of group activities with RKB

well-known manual assessment methods [22].

One extension of the KB approach for collaborative learning is the Reciprocal Kit-Build (RKB) [10], [11]. In standard KB, activities involve learners and their teachers who have different levels of expertise; in contrast, the RKB consists of a pair of learners. Figure 1 illustrates the sequence of RKB activities. Both learners create their map, then the system decomposes each map into a kit. Afterward, the kits are exchanged to enable each learner to build a reconstructual map of their partner's kit. The initial and the re-constructed maps are then compared using proposition-based similarity matching, as in the standard KB approach. The group members then have a discussion supported by the difference map visualization (i.e., matching, lacking, or excessive links).

The matching link represents an agreement between each pair which comes from the initial proposition that can be rebuilt by the partner, whereas the lacking link describes the initial proposition which cannot be reconstructed by the partner. The excessive link is a proposition that is created by the partner but not available in the initial map. Both lacking and excessive links represent disagreement between group members.

This visualization of similarities and differences exhibits conflicting ideas and triggers more questions and further discussion to resolve the conflicts. Hence, the RKB

approach aligns with the following collaborative learning processes: the externalization of thinking tasks; elicitation of knowledge; and conflict-oriented consensus building [4]. Lastly, the group members construct a collaborative map together (integration-oriented consensus building). An exploratory study conducted by [12] shows that the quality of students' collaborative products under this approach is significantly higher than that of their individual maps. The improvements also have a moderate positive correlation with the KB visualization of map differences.

2.3 Learning at Boundary with Reciprocal Kit Build

The KB approach can be categorized as more restrictive with regard to map contents than other common concept-map building approaches. The map components, collectively referred to as a kit, have a role as boundary objects to support communication between different members in a community of practice; e.g., between learners and teachers. The concept of boundary objects was introduced by Susan L. Star and James R. Griesemer in the field of sociology of science [23] as follows.

Boundary objects are objects which are both plastic enough to adapt to local needs and constraints of the several parties employing them, yet robust enough to maintain a common identity across sites. They may be abstract or concrete. They have different meanings in different social worlds, but their structure is common enough to more than one world to make them recognizable, a means of translation.

Prior research studies show that boundaries are not seen only as barriers to learning, but also as "spaces" with potential for learning [24], [25]. These studies argue that boundaries can operate as resources for development of intersecting identities and practices. Four learning mechanisms can take place at the boundary: identification, coordination, reflection, and transformation [24], [25].

Boundary crossing can lead to the identification of the intersecting practices, by which the natures of the practices are defined in relation to one another. It also can activate the coordination processes of both practices. Minimal routinized exchanges between practices are established to make transitions smoother, with boundary objects acting as mediating artifacts during coordination. Reflection is a profound effect of boundary crossing, which involves learning to look differently at one practice by taking on the perspectives provided by others. In the case of transformation, boundary crossing leads to changes in practices, and potentially even the creation of a new, "in-between" practice. Boundary objects can act as "reminders" that trigger relevant knowledge, or as "conversation pieces" that ground shared understanding, rather than as containers of knowledge [26].

Concept mapping using the RKB approach exemplifies learning activities with boundary objects. In the initial phase, the predefined nodes are the objects that can be used

to aid learners to get started, as well as to reflect on other group members' perspectives during reconstruction. Reconstruction is an active attempt to understand the group partner's representation, rather than simply reading a partner's map. After reconstruction, similar and different interpretations can be detected; therefore, reconstruction is an essential step that can be used to ground shared understanding and to trigger relevant knowledge, especially when conflicts are exhibited by showing the lacking and excessive links. The visualization of differences creates tensions and allows for discussion. Tensions can lead the activity to collapse, or can become reasons for change [27]. Finally, as evolving artifacts, the concept maps should be transformed into an integrated product that represents a group-level shared understanding. Group members negotiate and combine ingredients from different contexts to achieve hybrid solutions.

3. Methods

3.1 Participants and Instructional Context

Forty-four students of a Linear Algebra class participated in the current study. Most of them were first-year Computer Science students in a public university in Indonesia (number of male students: 32). The class was delivered in a blended-learning method, combining face-to-face and online classroom activities. Prior to the experiment, the students had been exposed to various collaborative learning activities, such as a jigsaw technique and an online discussion forum. With regard to concept mapping, the students had prior experience of building concept maps, both individually and collaboratively, from scratch.

In the Linear Algebra class, the students were learning about a new concept of a vector as an element of a vector space. During high school, the students had learned about a vector as a quantity having direction as well as magnitude. The new definition of vector required students to accommodate their prior knowledge. For the current study, the students were asked to create a concept map with their peers related to Inner Product Space and General Vector Space.

Before the experiment, the teacher had delivered introductory learning materials, and provided a set of keywords as predefined concepts ($n = 14$) to be included in their maps. Providing the initial concepts is an effective way to determine students' prior knowledge at the beginning of a task, and it is an influential factor in the learning process [16]. The experiment was conducted in a computer laboratory, and the students were allowed to choose to use their own laptops or the computers provided by the school. To make it convenient for the students to exchange knowledge and provide sufficient feedback to their partners, they were allowed to select their own partners.

3.2 Experimental Procedures

The experiment was held during two hours of a class session which was divided into three phases of activities: introduc-

Table 1 Timeline of students' activities during experiment

| Phase | Students' Activity | Duration |
|----------------------------|---|----------|
| Introduction Individual | Kit-Build practice | 5 min. |
| | Create a concept map based on the pre-defined concepts (first map) | 25 min. |
| Collaborative | Create a re-constructional map based on the partner's first map components (second map) | 20 min. |
| | Discussion on shared and difference maps | 10 min. |
| | Create a group concept map (third map) | 30 min. |

tion, individual, and collaborative phases. The class teacher played a role as the instructor while a researcher and three teaching assistants provided technical supports as needed. The teacher also did not provide any feedback related to contents of the map during the experiment session. The sequence of learners' activities and the activity duration are depicted in the Table 1. All participants completed each activity design within the timeframe.

During the introductory phase the teacher explained the overall learning activities and requested students to create a simple map by using a web-version of the RKB system. Next, at the individual phase, the students were asked to build their own concept maps based on the nodes given. After submission, the RKB system decomposed the map into a set of unconnected nodes and links (kit) and displayed it to the corresponding partner. The students reconstructed a new map based on the retrieved kit. After completing the map, the system performed a propositional-level matching between the first (initial) map and the second (reconstructed) map then presented the results to the students. This system feedback enabled students to detect similarities and differences between their representations and conduct a discussion during the collaborative phase. Finally, each group was requested to build a single map that represents their collaborative product.

3.3 Data Source and Measurements

3.3.1 Data Source

Knowledge convergence is divided into knowledge equivalence and shared knowledge, which can be evaluated prior to, during, and/or after collaboration [28]. Knowledge equivalence refers to learners in a group possessing a similar degree of knowledge related to a specified subject, regardless of the specific concepts constituting the knowledge content [28]. While shared knowledge alludes to the knowledge of specific concepts that learners within a group have in common [28]. This study evaluates knowledge convergence at a group level prior to collaboration, based on the definition of shared knowledge on the assigned task.

All students' individual maps (i.e., the first and second maps), and the collaborative group maps, were recorded through a web-based RKB system. The similarities and differences among group members or between individual maps and the group map were measured to determine the simi-

larity of knowledge and potential knowledge transfer from individual inputs. The similarity of knowledge at structural and semantic levels was calculated automatically based on the map links and linking words [29]. Moreover, as an expert, the class instructor was responsible for assessing all students' individual and group maps based on the completeness and correctness of the information presented. The change of map scores was analyzed to determine group learning achievements by using a normalized change formula [30].

3.3.2 Similarity of Students' Prior Knowledge Before Collaboration

The similarity of individual prior knowledge is investigated based on the students' first maps. A concept map can be represented as a graph, hence graph similarity measures can be used to identify the similarity between map elements such as nodes and links. In this study, since all individuals' maps consist of pre-defined nodes, the similarities and differences regarding individual knowledge representation are portrayed based on the map links and their corresponding linking words.

The concept map similarity measures are adopted from the formula used by Ifenthaler [13], which follows the similarity definition proposed by Lin [31]; that a similarity between objects A and B is related to their commonality and the differences between them. The maximum similarity between objects A and B is reached when A and B are identical, regardless of how much commonality they share. The similarity between A and B is measured by the ratio between the amount of information required to state the commonality of A and B and the information needed to fully describe what A and B are [31].

A graph $G = (V, E)$ is a finite set V of n nodes and a set E of edges, where E is a subset of $V \times V$. Given two undirected and labeled graphs, $A = (V, E_A)$ and $B = (V, E_B)$, with common node set V , $S(A, B)$ is the similarity between A and B as measured by S . SE_{AB} consists of shared links between E_A and E_B while UE_{AB} contains a set of unshared links created by only one of the group members.

$$SE_{AB} = E_A \cap E_B \quad (1)$$

$$UE_{AB} = E_A \ominus E_B \quad (2)$$

$$S(A, B) = \frac{|SE_{AB}|}{|SE_{AB}| + \frac{|UE_{AB}|}{2}} \quad (3)$$

The current study only considered structural similarity as in Eq. (3) to measure the similarity between two concept maps since it represents the whole structure of the maps as graphs. The score is defined on a scale between 0 (no structural similarity between two maps) and 1 (absolute similarity between two maps).

Further investigation on the similarity of a pair's linking words is also carried out to discover semantic similarity between two individual maps. However, this measurement only covers common map elements that were defined by the

students, such as the shared links. The similarity of linking words is calculated by employing the Term Frequency-Inverse Document Frequency (TF-IDF) cosine similarity formula [29] for each shared link on the first maps. This approach is widely used to establish the similarity between two texts. It can be categorized as a lexical similarity approach based on character and statement matching. To enhance the quality of measurement, some text pre-processing techniques are applied, such as text normalization (e.g., transforming to lower case, removing punctuation, stemming) and stop-word removal. Using the TF-IDF cosine similarity formula, the similarity score is between 0 and 1. In addition, linking-word similarity falls into three following categories: **no similarity** if the score is 0; **moderately low similarity** if the score lies between 0–.509; and **moderately high similarity** if greater than .509. This categorization is based on the first and third quartiles of the similarity score distribution ($M = .27, SD = .34, Q1 = 0, Q3 = .509$). The first quartile ($Q1$) is the middle number between the smallest number and the median of the data set, while the third quartile ($Q3$) is defined as the middle number between the median and the highest number of the data set.

3.3.3 Comprehension of The Partner's Map Components

Comprehension of the components of the partner's map represents how effectively an individual can express their understanding of their partner's map components (nodes and links), in the form of a concept map. Since the list of concepts is defined by the teacher, the measurement only considers the reconstructed partner's links.

A graph $G_A = (V, E_A)$ is a finite set V of n nodes and a set E of edges built by student A . A graph $R_A = (V, E_{RA})$ is a graph re-constructed by student A 's partner. Let E_{MA} be the set of A 's first map links that are connected to the same nodes by the partner in the second map, while E_{NA} consists of the links that are joined to different nodes.

$$E_{MA} = E_{RA} \cap E_A \quad (4)$$

$$E_{NA} = E_{RA} \ominus E_A \quad (5)$$

The element of E_{MA} is called a reconstructed link, while E_{NA} consists of non-reconstructed links. Given two undirected and labeled re-constructional graphs R_A and R_B with common node set V , $C(A, B)$ is the comprehension value between student A and B , as a pair in a group, defined as:

$$C(A, B) = \frac{|E_{MA} + E_{MB}|}{|E_{MA} + E_{MB}| + \frac{|E_{NA} + E_{NB}|}{2}} \quad (6)$$

3.3.4 Transfer of Elements from Individual to Group Maps

The transition (or change) of elements from the first maps to the second maps and the group maps provides a deeper understanding of how the individuals build on each other's ideas to construct a collaborative product. The transfer of elements is indicative of an individual's input in the group solution. The number of concepts in the group solution that

exist in at least one of the group member's individual maps is used in [32] to measure individual-to-group transfer.

In the current study, link connections and linking words are considered as elements for measuring transfers. The number of individual map links, both shared and unshared, accepted as components for the group map describes the transfer of link elements. From those transferred links, the corresponding linking words in the individual and group maps are extracted to measure semantic similarity. By applying the TF-IDF cosine similarity formula [29]) and some pre-processing techniques, the similarity score is calculated. The similarity value is from 0 to 1 inclusive, with the mean of .68 and standard deviation of .37. Furthermore, the first and third quartiles of the data distribution are used to define thresholds for categorization ($Q1 = .366, Q3 = 1$). The categories of individual-to-group linking word similarity are as follows:

- **follow initial:** the group of linking words that are similar with at least one of the individual linking words (similarity value of equal to or more than .99);
- **modify initial:** the group of linking words that are modified from one of the individual linking words (similarity value above .366 and below .99);
- **new:** the group of linking words that are not similar to any of the individual linking words (similarity value of below .366).

3.3.5 Group Learning Achievements: Map Score Change

To measure the change of map score from the individual to the collaborative phase, this study adopts the normalized change formula proposed by Marx and Cummings [30]. The procedure involves the ratio of the gain to the maximum possible gain, or the loss to the maximum possible loss. If the gain is zero, the normalized change $c = 0$, except when a student earns a zero or a perfect score on the pre-test and post-test. Since this study aims to investigate the learning outcomes at the group level, the average of individuals' first map score is defined as the pre-score, while the final collaborative map score is regarded as the post-score. Let ais represent the average of individual (first) map score, and gms represent the final collaborative map score for each group. The normalized score gain (c) is defined as follows.

$$c = \begin{cases} \frac{gms-ais}{100-ais} & \text{if } gms > ais \\ \text{drop} & \text{if } gms = ais = 100 \text{ or } 0 \\ 0 & \text{if } gms = ais \\ \frac{gms-ais}{ais} & \text{if } gms < ais \end{cases} \quad (7)$$

4. Results

4.1 Relationship Between Group Prior Knowledge Similarity, Comprehension of the Partner's Kit, and Map Score Change

Table 2 summarizes the descriptive statistics of the similar-

Table 2 Descriptive statistics

| Data | <i>M</i> | <i>SD</i> | <i>Min</i> | <i>Max</i> |
|------------|----------|-----------|------------|------------|
| $S(A, B)$ | .47 | .27 | 0 | .93 |
| $C(A, B)$ | .85 | .12 | .65 | 1 |
| <i>ais</i> | 72.21 | 18.22 | 41.43 | 98.57 |
| <i>gms</i> | 90 | 7.31 | 75.71 | 100 |
| <i>c</i> | .54 | .34 | -.09 | 1 |

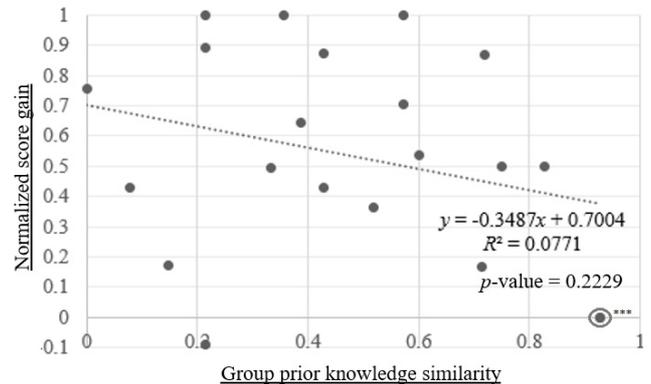


Fig. 2 Scatter plot of group prior knowledge similarity and normalized gain from individual to collaborative map

ity ($S(A, B)$), comprehension level ($C(A, B)$), and the average individual score (ais), group map score (gms), and normalized change (c). From the 22 groups of participants, one group should be omitted from the analysis because they achieved perfect scores on both the ais and gms . A paired-samples t-test is conducted to compare the group average individual score and the group map score. There is a significant difference between the average individual score ($M = 72.21, SD = 18.22$) and the group map score ($M = 90, SD = 7.31$); $t(20) = 4.92, p < .01$. These results show that in general, the collaborative outcomes increased. Eighteen groups showed better group map outcomes, two groups retained the same scores, and one group received a lower score. The detail of changes of map qualities from individual maps to group map is presented in [12].

Figure 2 depicts the distribution of the group's prior knowledge similarity (Eq. (3)) and normalized score gain from individual to group map (Eq. (7)). Two groups have the same similarity value and normalized gain, ($S(A, B) = .93, c = 0$). This duplicate score is marked with a double circle and asterisk symbol (***) in Fig. 2. Based on the structural similarity of the first individual maps, there are 6 groups with similarity values of equal to or more than .714, 9 groups with similarity values between .214 and .714, and the other 6 groups have lower similarity values. The variable group prior knowledge similarity and normalized score gain are found to be weakly negatively correlated, $R(19) = -.278, p = .22$.

Figure 3 shows correlation between the comprehension level of the partner's representation (Eq. (6)) and normalized score gain (Eq. (7)). The comprehension of the partner's presentation and normalized score gain are moderately negatively correlated, $R(19) = -.51, p < .05$. As comprehension

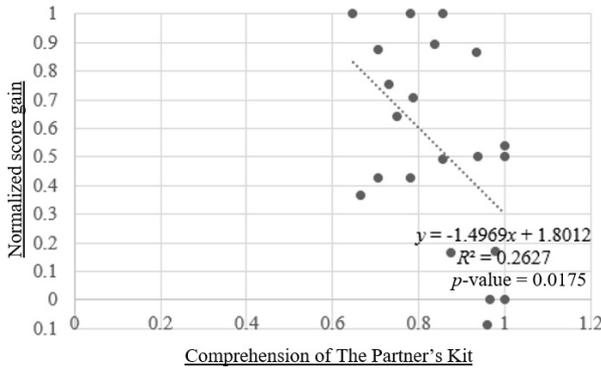


Fig. 3 Scatter plot of group comprehension level and normalized gain from individual to collaborative map

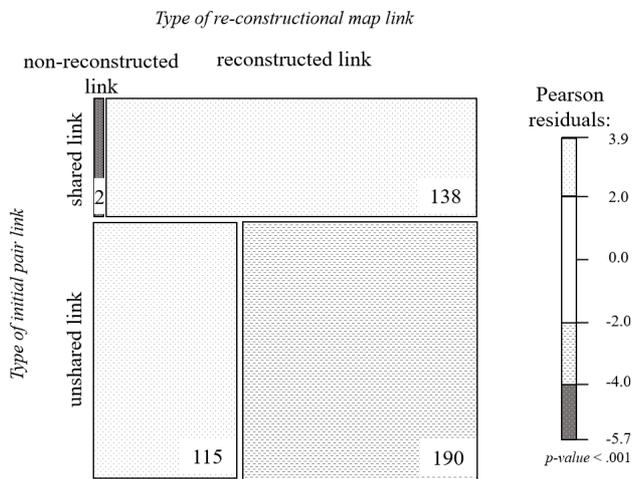


Fig. 4 Mosaic plot of similarity of prior knowledge and comprehension of partner's kit

increases, normalized change decreases. Though the similarity of prior knowledge and comprehension of the partner's map elements show a moderately positive correlation with significant coefficient, $R(19) = .47, p < .05$, comprehension level is a stronger predictor than level of similarity of prior knowledge for normalized score gain. Both Fig. 2 and 3 depict the new results presented by the current study.

In total, over 445 unique links are written by the students in their first maps (see Fig. 4). Thirty-one percent of those links belong to shared links ($n = 140$), while the remaining links are unshared ($n = 305$). Almost all shared links can be reconstructed (99%, $n = 138$). Some unshared links can also be reconstructed (62%, $n = 190$). The number of unshared links which can be reconstructed is higher than that for non-reconstructed links ($n = 115$).

4.2 Individual Contributions to Collaborative Products

In this subsection, the similarity levels between the actual collaborative product and each group member's individual map are compared. Figure 5 depicts the distribution of shared, unshared, reconstructed, and non-reconstructed links across all group maps. The total number of group links generated by the 21 groups of students is 307, of which 92%

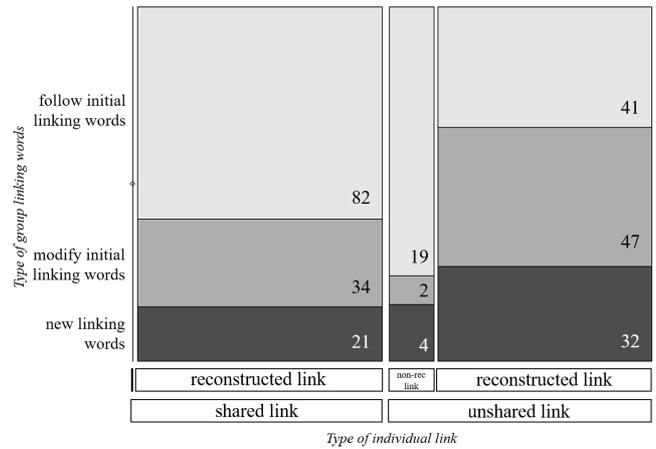


Fig. 5 Source of group map components

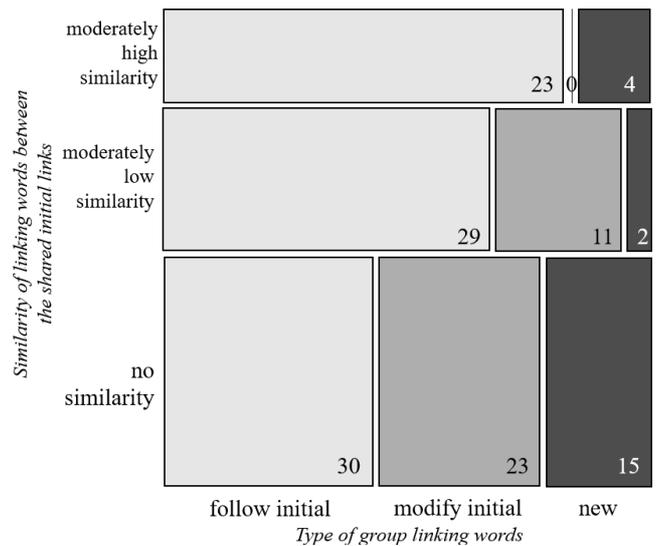


Fig. 6 Transfer of individual linking words to group map

($n = 282$) resembles the first map's links. Both shared and unshared links contributed proportionally to the group map ($n = 137$ and $n = 145$, respectively). The number of shared and unshared links is different from the one in Sect. 4.1 because not all individual links were composed in the group maps. The reconstructed shared and unshared links were more likely to be accepted than the group links. None of the non-reconstructed shared links are represented among the group links, and few of the non-reconstructed unshared links are available in the group maps (17%, $n = 25$ out of 145). Further, about 8% of the group links are newly generated links. Since most of the group links are similar to the initial links in the students' first maps, the similarity levels between the linking words of the initial and the group links are measured. The distribution of linking-word similarity among different types of links is also presented in Fig. 5.

Moreover, Fig.6 shows how the students employed linking words from the initially shared links to compose group propositions. When the similarity of initial linking words is moderately high, the tendency is to use any group

member's initial linking words without modifications. In cases when the similarity is moderately low, any of the group member's linking words could be chosen (69%, $n = 29$). However, the tendency is to modify or create new linking words (56%, $n = 38$) when there is no similarity.

5. Discussion

The results indicate that there is an improvement in the generated map based on expert judgement and normalized change measurement ($M = .54, SD = .34$), as shown in Table 2. Further, Pearson's correlation analysis shows that comprehension level and normalized change of products from individual to group level shows a moderately negative correlation, with a significant coefficient, while similarity of prior knowledge reveals a weaker correlation with normalized change. The results show that the comprehension of the partner's representation is a stronger predictor to detect the normalized change when compared to the similarity of prior knowledge.

The similarity between the individual and group maps represents individual input to the group outcome. Providing a set of disconnected partner's map components prompted students to reflect their understanding of their partner's representation. A Wilcoxon signed-rank test indicates that the median of the similarity score between students' second maps and their partners' first maps ($Mdn = .746$) is significantly higher than the median of the similarity score between students' second and first maps ($Mdn = .6$), $Z = 224.5, p < 0.01$. This illustrates that, when students reconstructed their partners' components, they were making an effort to understand their partners' maps, rather than to express their own initial maps by using new components. In this context, the map components function as boundary objects that can be operated to identify similarities or differences in perspectives, and as mediating artifacts during coordination. Furthermore, boundary-crossing activities may lead to changes in practice (transformation of knowledge) [25].

Surprisingly, the results also show that the numbers of shared and unshared links in the group solutions are proportionally distributed. While constructing a group map, the students were tempted to manipulate their first map components rather than creating new links. This is an indication that the students were reflecting on their individual available knowledge to construct the group product. The results also demonstrate a considerable number of reconstructed unshared links in the group map, which could indicate that the students were able to accept reconstructed elements as parts of group solutions, although they involved different representations. Many initial linking words with zero similarity scores from the shared links were modified, which reveals that the students attempted to resolve conflicts regarding different link definitions. In contrast, the individual linking words with higher similarity scores were more likely to be included in the group map without any modification. Figure 7 shows an example of the transformation

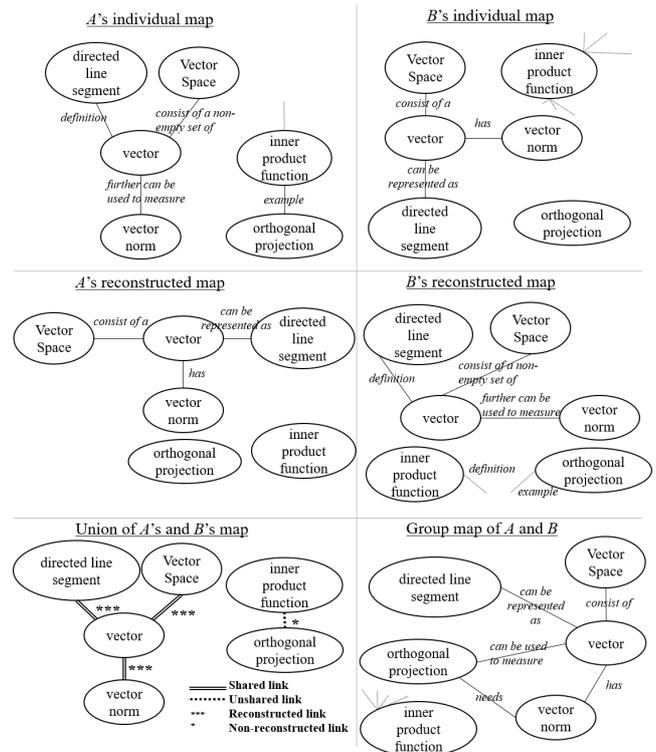


Fig. 7 Sample of individual maps of two students in a group, their reconstructed maps, the corresponding union map with the categorization of links, and the newly transformed group map

from individuals to group following the unshared or non-reconstructed links; i.e., related to the node of orthogonal projection. In the group map that link connection differs from any existing individual map components. The incorrect knowledge on the individual maps was finally corrected through the collaborative activity.

Allowing students to review all members' first maps, as a form of access to distributed cognitive resources, should positively affect the broadness of group problem solutions [32]. To support the creation and evolution of active boundary objects, Fischer suggests providing systems that can create awareness of each other's work among group members, afford opportunities for individual reflection and exploration, enable co-creation, allow participants to build on the work of others, and provide mechanisms to help draw out tacit knowledge and perspectives [26]. Reconstruction and discussion supported with the difference map during the RKB activities trigger reflection and exploration activity, enabling group members to review each other's representation. Also, such an approach may potentially foster knowledge convergence after collaboration; that is, the similarity of knowledge possessed by group members after collaborative learning [28]. Interdependence exists between the effectiveness of group and individual learning, and more successful groups are more beneficial to their members as individuals [32].

The current study's results have been derived based on the group learning outcomes; however, further investi-

gation of the effect at the individual level is important. This study excluded consideration of the effectiveness at the level of the individual since we did not collect individual post-collaboration maps, due to time limitations enforced by conducting the experiment in a practical classroom. The similarity between the group and individual post-collaboration maps represents the knowledge that is transferred from the shared group cognition to individual cognition, and is indicative of individual learning outputs [32].

6. Conclusion

The present study conducted an investigation on how the similarity of individual prior knowledge and the comprehension of partner's representation during the RKB activities may influence the students' final collaborative outcome. The results of this investigation show that the comprehension of partner's representation in the form of reconstruction is a stronger predictor for estimating score gain, rather than the similarity of prior knowledge. Reconstruction triggers learners' interaction by providing the boundaries for students to operate on their initial knowledge. Similarities in prior knowledge may influence the broadness of group solutions. In addition, the evaluation of partner comprehension through reconstruction has potential for encouraging further modification of individual knowledge.

One of the more significant findings to emerge from this study is that students work on their individual ideas during the collaborative phase. They utilize their initial shared and unshared knowledge when building collaborative products. A considerable number of reconstructed links dominate the final group maps, despite the similarity of links. Different linking words are more likely to be modified, while the highly similar ones are easily accepted as it is. Active reviewing on individual ideas has the potential to foster knowledge convergence after collaboration. However, the current study has not addressed it yet. A future study investigating the analysis of knowledge similarity after collaboration is needed to reveal the effect of the RKB approach at the individual learning achievements. Another limitation of this study is that the number of participants and course subjects were relatively small. Further research needs to be done with more participants and various course topics.

The findings of this study have some important implications for future practice. This study suggests developing a feedback system based on the similarity of prior knowledge and the comprehension of the partner's representation. The system could provide a recommendation for the teacher to form a group in consideration of the similarity of initial maps. Moreover, the teacher may utilize the results of reconstruction to predict the group outcomes. If necessary, specific treatment should be provided to assist learners who face difficulties to progress. In addition, the system may display an integrated difference map to support learners in accommodating different representations while composing a group map. The integrated map could show the reconstructed and non-reconstructed elements. A recommendation to select or

modify the initial linking words could be useful to enhance the final results and reduce the time necessary to construct a group map. Combining different perspectives is a challenging task for the students. If this process is supported, the number of transfers from group to individual cognition would be potentially increasing. Hence, fostering knowledge convergence after collaboration.

Acknowledgments

This work was partially supported by JSPS KAKENHI Grant Numbers 19H04227 and 17H01839.

References

- [1] H. Jeong and M.T.H. Chi, "Knowledge convergence and collaborative learning," *Instructional Science*, vol.35, no.4, pp.287–315, 2007.
- [2] E. Baines, C. Rubie-Davies, and P. Blatchford, "Improving pupil group work interaction and dialogue in primary classrooms: results from a year-long intervention study," *Cambridge Journal of Education*, vol.39, no.1, pp.95–117, 2009.
- [3] J. Roschelle, "Learning by collaborating: Convergent conceptual change," *The Journal of the Learning Sciences*, vol.2, no.3, pp.235–276, 1992.
- [4] F. Fischer and H. Mandl, "Facilitating knowledge convergence in videoconferencing environments: the role of external representation tools," *Proc. Conference on Computer Support for Collaborative Learning: Foundations for a CSCL Community*, pp.623–624, 2002.
- [5] C. van Boxtel, J. van der Linden, E. Roelofs, and G. Erkens, "Collaborative concept mapping: Provoking and supporting meaningful discourse," *Theory Into Practice*, vol.41, no.1, pp.40–46, 2002.
- [6] C. van Boxtel, J. van der Linden, and G. Kanselaar, "Collaborative learning tasks and the elaboration of conceptual knowledge," *Learning and Instruction*, vol.10, no.4, pp.311–330, 2000.
- [7] P.J. Beers, H.P.A. Boshuizen, P.A. Kirschner, and W.H. Gijssels, "Common ground, complex problems and decision making," *Group Decision and Negotiation*, vol.15, no.6, pp.529–566, 2006.
- [8] C.H. Chiu, "Exploring how primary school students function in computer supported collaborative learning," *International Journal of Continuing Engineering Education and Life Long Learning*, vol.13, no.3-4, pp.258–267, 2003.
- [9] W.-M. Roth and A. Roychoudhury, "The social construction of scientific concepts or the concept map as device and tool thinking in high inscription for social school science," *Science Education*, vol.76, no.5, pp.531–557, 1992.
- [10] W. Wunnasri, J. Pailai, Y. Hayashi, and T. Hirashima, "Reciprocal Kit-Build concept map: An approach for encouraging pair discussion to share each other's understanding," *IEICE Trans. Inf. & Syst.*, vol.E101-D, no.9, pp.2356–2367, 2018.
- [11] W. Wunnasri, J. Pailai, Y. Hayashi, and T. Hirashima, "Reciprocal Kit-Building of concept map to share each other's understanding as preparation for collaboration," *Proc. 19th International Conference on Artificial Intelligence in Education, London, United Kingdom, 2018*.
- [12] L. Sadita, T. Hirashima, Y. Hayashi, W. Wunnasri, J. Pailai, K. Junus, and H.B. Santoso, "Preliminary study on the use of reciprocal kit build for collaborative learning," *Proc. 26th International Conference on Computers in Education (ICCE 2018)*, pp.133–142, 2018.
- [13] D. Ifenthaler, "Relational, structural, and semantic analysis of graphical representations and concept maps," *Educational Technology Research and Development*, vol.58, no.1, pp.81–97, 2010.
- [14] T. Hirashima and Y. Hayashi, "Educational externalization of think-

ing task by Kit-Build method," *Human Interface and the Management of Information: Applications and Services*, ed. S. Yamamoto, Cham, vol.9735, pp.126–137, Springer International Publishing, 2016.

- [15] J.D. Novak and D.B. Gowin, *Learning How to Learn*, Cambridge University Press, 1984.
- [16] A.J. Cañas, J.D. Novak, and P. Reiska, "Freedom vs. restriction of content and structure during concept mapping - Possibilities and limitations for construction and assessment," *Proc. Fifth Int. Conference on Concept Mapping*, 2012.
- [17] C. Gracia-Moreno, J.-F. Cerisier, B. Devauchelle, F. Gamboa, and L. Pierrot, "Collaborative knowledge building through simultaneous private and public workspaces," *Data Driven Approaches in Digital Education*, vol.10474, pp.553–556, 2017.
- [18] T. Engelmann and F.W. Hesse, "How digital concept maps about the collaborators' knowledge and information influence computer-supported collaborative problem solving," *International Journal of Computer-Supported Collaborative Learning*, vol.5, no.3, pp.299–319, 2010.
- [19] T. Hirashima, K. Yamasaki, H. Fukuda, and H. Funaoi, "Framework of Kit-Build concept map for automatic diagnosis and its preliminary use," *Research and Practice in Technology Enhanced Learning*, vol.10, no.1, p.17, 2015.
- [20] T. Hirashima, "Reconstructional concept map: Automatic assessment and reciprocal reconstruction," *Proc. 2nd Annual International Conference Learning Innovation*, 2018.
- [21] J. Pailai, W. Wunnasri, K. Yoshida, Y. Hayashi, and T. Hirashima, "The practical use of Kit-Build concept map on formative assessment," *Research and Practice in Technology Enhanced Learning*, vol.12, no.1, p.20, 2017.
- [22] W. Wunnasri, J. Pailai, Y. Hayashi, and T. Hirashima, "Validity of Kit-Build method for assessment of learner-build map by comparing with manual methods," *IEICE Trans. Inf.& Syst.*, vol.E101-D, no.4, pp.1141–1150, 2018.
- [23] S.L. Star and J.R. Griesemer, "Institutional ecology, 'translations' and boundary objects: Amateurs and professionals in Berkeley's museum of vertebrate zoology, 1907-39," *Social Studies of Science*, vol.19, no.3, pp.387–420, 1989.
- [24] S.F. Akkerman and A. Bakker, "Boundary crossing and boundary objects," *Review of Educational Research*, vol.81, no.2, pp.132–169, 2011.
- [25] S.F. Akkerman, "Learning at boundaries," *International Journal of Educational Research*, vol.50, no.1, pp.21–25, 2011.
- [26] G. Fischer, E. Giaccardi, H. Eden, M. Sugimoto, and Y. Ye, "Beyond binary choices: Integrating individual and social creativity," *International Journal of Human Computer Studies*, vol.63, no.4-5, pp.482–512, 2005.
- [27] Y. Engeström, "Developmental studies of work as a testbench of activity theory: The case of primary care medical practice," in *Understanding Practice: Perspectives on Activity and Context*, ed. S. Chaiklin and J. Lave, pp.64–103, Cambridge University Press, 1993.
- [28] A. Weinberger, K. Stegmann, and F. Fischer, "Knowledge convergence in collaborative learning: Concepts and assessment," *Learning and Instruction*, vol.17, no.4, pp.416–426, 2007.
- [29] G. Qian, S. Sural, Y. Gu, and S. Pramanik, "Similarity between Euclidean and Cosine Angle Distance for nearest neighbor queries," *Proc. ACM Symposium on Applied Computing*, pp.1232–1237, 2004.
- [30] J.D. Marx and K. Cummings, "Normalized change," *American Journal of Physics*, vol.75, no.1, pp.87–91, 2007.
- [31] D. Lin, "An information-theoretic definition of similarity," *Proc. of the Fifteenth International Conference on Machine Learning, ICML '98*, San Francisco, CA, USA, pp.296–304, 1998.
- [32] N. Stoyanova and P. Kommers, "Concept mapping as a medium of shared cognition in computer-supported collaborative problem solving," *Journal of Interactive Learning Research*, vol.13, no.1, pp.111–133, 2002.



collaborative learning, learning analytics, online education, and human-computer interaction.

Lia Sadita received her B.Comp.Sc. degree from Universitas Indonesia in 2009 and M.Eng. degree from Korea University of Science & Technology in 2013. During 2013–2017, she worked at the Faculty of Computer Science, Universitas Indonesia as a teaching assistant and junior lecturer. She is now a doctoral student in Hiroshima University with research works on computer-supported collaborative learning and re-constructional concept mapping. She is interested in topics related with



Pedro Gabriel Fonteles Furtado received his Master of Engineering degree at Hiroshima University in 2017 and remains there as a Ph.D. student. Pedro has contributed in the field of Computers in Education with research regarding serious games for improving foreign language inferring and for teaching arithmetic word structure to young children. He is currently interested in gameful design, computer-assisted vocabulary learning and flow state oriented design.



since 2004. Learning Engineering is his major research field. He has received international awards as the Outstanding Paper Award of EDME-DIA95, the Best Paper Award of ICCE2001 & 2002, Honorable Mention Award of AIED2009, APSCE Distinguished Researcher Award in 2009, and the ICCE2015 Best Technical Design Paper Award.

Tsukasa Hirashima received his B.E., M.E. and Ph.D. from Osaka University in 1986, 1988, and 1991, respectively. He worked at The Institute of Scientific and Industrial Research, Osaka University as a research associate and lecturer from 1991 to 1997. During 1997–2003, he worked in the Graduate School of Information Engineering at Kyushu Institute of Technology as an associate professor. He has been a professor of the Graduate School, Department of Information Engineering, Hiroshima University



an associate professor of the Information Technology Center, Nagoya University from 2010 to 2012. He has been engaged in research on Knowledge modeling, Ontological engineering, and Learning engineering. He has received international awards as the Best Paper Award of ICCE2006 and the Best Technical Design Paper Award of ICCE2015.

Yusuke Hayashi is an associate professor of the Graduate School of Engineering at Hiroshima University, ever since 2012. He received his Ph.D. from the Graduate School of Engineering Science, Osaka University, Japan, in 2003. He was a research associate of the school of Knowledge Science, Japan Advanced Institute of Science and Technology (JAIST) from 2003 to 2005, an assistant professor of the Institute of Scientific and Industrial Research (ISIR), Osaka University from 2005 to 2010 and