DRAFT
INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED'07
28 - 31 AUGUST 2007, CITE DES SCIENCES ET DE L'INDUSTRIE, PARIS, FRANCE

LEARNING SUPPORT FOR COMPOSITION ABILITY: SURFACE AND STRUCTURAL SIMILARITY

Junya Morita[1], Yukari Nagai[1] and Toshiharu Taura[2]
[1]School of Knowledge Science, Japan Advanced Institute of Science and Technology
[2]Graduate School of Engineering, Kobe University

ABSTRACT
Composition ability is one of the basic skills in design work, which is the combining of parts to form a whole. This paper introduces a support system helps learners acquire the ability to compose consistent figures. Our system is an application of the model of analogical reasoning. The system presents an example graphic and prompts the learner to compose a novel one. After it calculates scores for the surface and structural similarities of the graphic composed by the learner and the example presented by the system, the system gives the scores to the learner as feedback in order to help the learner extract abstract principles from the presented example. This paper presents the algorithms of the model and the results of experiment that investigate the correspondence between human similarity rating and the scores calculated by the model.

Keywords: Design education, analogical reasoning, graphic compositions

1 INTRODUCTION
One of the basic skills in design work is the ability to construct consistent figures by controlling the attributes of objects in them. Graphic designers compose two-dimensional images, and architectural and engineering designers compose three-dimensional structures. In both situations, well-designed products are composed by assuring that each of the attributes is consistent with the others and that all of them are suited to design requirements.
One way to acquire this skill is through learning by example. As the proverb "a picture is worth a thousand words" indicates, it might be difficult to communicate visual information verbally [10]. Composition can therefore be assumed to be learned more effectively by observation than by verbal instruction.
Implicit in the proverb, however, is one of the problems with learning by example. If it were literally true, there would be a thousand features in a visual example. In this type of situation, the question that would arise would be, which features should the learner focus on? Obviously, it is necessary for an effective learning support system to help a learner gain an adequate perspective of an example.
This paper is motivated by the above problem. We describe a learning system for composition, one that presents the learner with an example graphic and prompts the learner to compose a one. Once the learner completes the task, the system automatically calculates scores for two kinds of similarity between the graphic composed by the learner and the example presented by the system. It then gives the scores to the learner as learning feedback. We think that this feedback helps the learner obtain appropriate perspectives on graphic spaces.

2 HYPOTHESIS
As noted earlier, learning by examples has a problem with the perspective settings. In this section the problem is considered from the viewpoint of analogical reasoning. Analogical reasoning is an activity constructing a mapping from the known *base domain* to the novel *target domain* [6]. This type of activity has been intensively investigated in the research field of cognitive science. The main problem of focus has been on the constraints imposed on analogical reasoning. Since numerous commonalities can be found between any two domains, it is impossible to construct a mapping without constraints that can determine the similarities between two domains.

We propose a method of learning by example that applies the findings of studies on analogical reasoning, because the problems underlying analogical reasoning can be assumed that the same as those underlying learning by example. Past studies have revealed that among the constraints on analogical reasoning are the following two types of similarities [2, 5].

- Surface similarity: the base and the target share attributes.
- Structural similarity: the base and the target have a relational structure in common.

Psychological experiments have shown that these two types of similarities influence different aspects of human cognition. People tend to notice surface features immediately but in certain situations they give greater weight to structural similarity [7, 12]. More precisely, surface similarity mainly influences lower-level cognition—such as that involved in instant perception and in retrieving or associating examples from memory—whereas structural similarity influences higher-order cognition like that involved in for problem solving and scientific discovery.
We think the distinction between the two types of similarity is also important in the field of design education and have therefore posited the following hypotheses.

- Learners tend to focus on the surface features of objects, such as colour or shapes.
- The important features in composition are not the surface features but the structure ones, such as distance, balance, and the combinations of shapes.

These hypotheses are consistent with the definition of composition. The combination of elements in graphic design can be considered the association of structural features in analogical reasoning. The present paper describes a learning support system that is based on these hypotheses and incorporates an analogical reasoning model computing the surface and structural similarities of graphics.

3 LEARNING SUPPORT SYSTEM

In this section, we describe a learning system of graphic composition. Figure 1 shows the system overview and Figure 2 shows its user interface. This section describes the four main components of the system: (1) the design environment, (2) the example presentation, (3) the propositional representation, and (4) the similarity scoring.

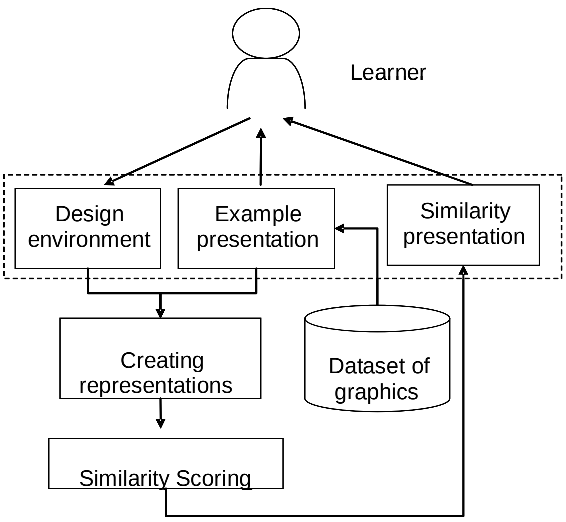


Figure 1: System overview.

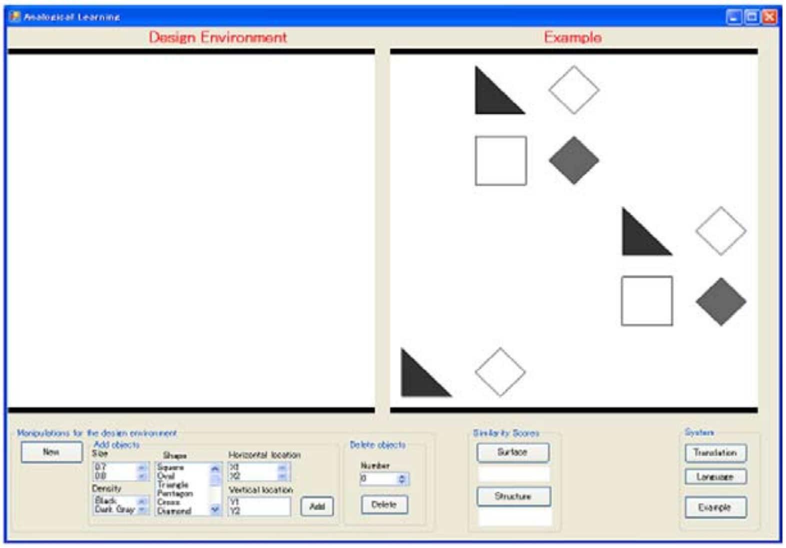


Figure 2: User interface for system.

3.1 Design environment

The system provides a design environment in which the learner composes a graphic on a 5-by-5 matrix by placing several objects on the grids. The system provides scrolling menus for assigning the following attributes to the objects.

- Location
  The learner can choose the objects' locations on the horizontal and vertical axes. Two objects in this environment cannot share the same location.
- Size
  The size of the objects can be chosen from five values ranging from 175 to 250 pt.
- Density
  The colour density of the objects can be chosen from five values ranging from white to black.
- Shape
  The shape of the objects can be chosen from sixteen types including ovals, rectangles, rectangular triangles, and parallelograms.

Although this environment is extremely simple, it is consistent with the composition tasks used in the real-world design education. Figure 3 shows a work created in a composition task in a school of ceramic design. It was created by placing several geometric shapes on a piece of paper.

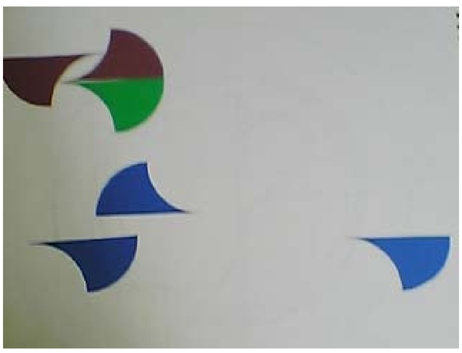


Figure 3: Example of a graphic composition.

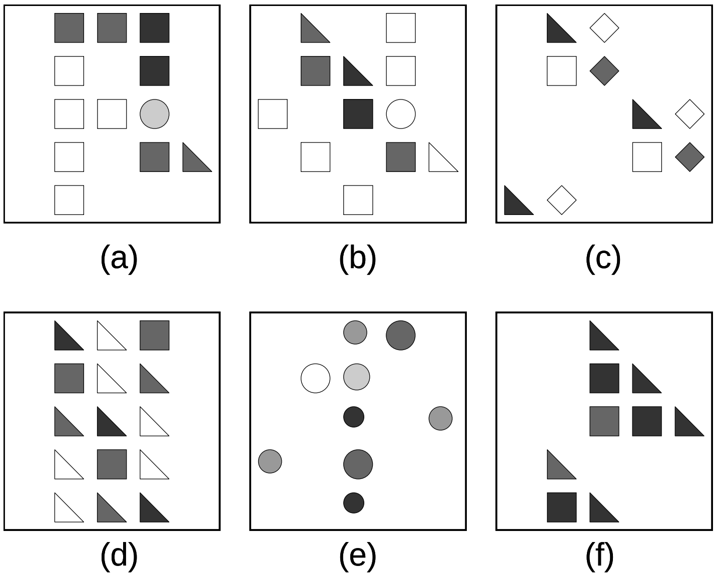


Figure 4: Examples of graphics.

3.2 Examples

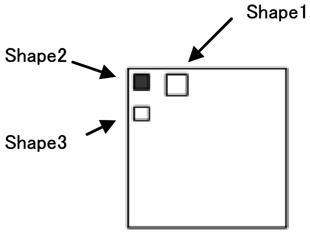
The learner considers an example presented in the example presentation window. It is chosen from a dataset including the graphics shown in Figure 4. These graphics were composed by the creator of the composition shown in Figure 3.

3.3 Representations

The system computes two types of similarities between the example and the graphic composed by the learner. The calculation of the two types of similarities uses a common scheme that represents a visual scene as propositions (predicate calculus). The representation is developed through the following two steps.

1. Representing attributes
   The system inspects the properties of each of the objects in the graphic and creates a set of propositions whose predicates indicate the attributes of the objects.
2. Representing relations
   The system inspects the proposition of the attributes to construct propositions of the relations between the two objects. Every possible combination of objects is inspected.

Figure 5 presents an example of the developed representations. The graphic contains three objects: “Shape1,” “Shape2,” and “Shape3.” The attributes of each object are represented in “Propositions of attributes,” and the relations of every possible combination of objects are represented in “Propositions of relations.”
As shown in the figure, in our scheme the predicates do not take a specific value as an augment (e.g., *(x Shape1 2)*, *(distance Shape1 Shape2 1)*) but instead indicate the values directly. For example, the proposition *(2x Shape1)* means that the object “Shape2” is located in the second column of the graphic. The proposition *(1distance Shape1 Shape2)* means that “Shape1” is next to “Shape2”.
Our representational scheme has the advantage of distinguishing the propositions of attributes from those of relations. The propositions of attributes are always described with one-place predicates, whereas the propositions of relations are described with two-place predicates.




```
;;Propositions of Attributes
;Attributes of Shape1
(2x Shape1)
(1y Shape1)
(4size Shape1)
(5darkness Shape1)
(rectangle Shape1)
;Attributes of Shape2
(1x Shape2)
(1y Shape2)
(1size Shape2)
(1darkness Shape2)
(rectangle Shape2)
;Attributes of Shape3
(1x Shape3)
(2y Shape3)
(1size Shape3)
(5darkness Shape3)
(rectangle Shape3)

;; Propositions of Relations
;Relations between Shape1 and Shape2
(horizontal Shape1 Shape2)
(1distance Shape1 Shape2)
(4dens_difference Shape1 Shape2)
(3size_difference Shape1 Shape2)
(same_shape Shape1 Shape2)
;Relations between Shape1 and Shape3
(right_up Shape1 Shape3)
(1distance Shape3 Shape1)
(0dens_difference Shape3 Shape1)
(3size_difference Shape1 Shape3)
(same_shape Shape3 Shape1)
;Relations between Shape2 and Shape3
(vertical Shape2 Shape3)
(1distance Shape3 Shape2)
(4dens_difference Shape3 Shape2)
(0size_difference Shape3 Shape2)
(same_shape Shape3 Shape2)
```

Figure 5: Example of representations.

3.4 Similarity scoring

The two types of similarity scores are calculated by using the above representation. The calculation of the surface similarity uses the representations of the attributes. The calculation of the structural similarity uses the representations of the relations.

Surface Similarity

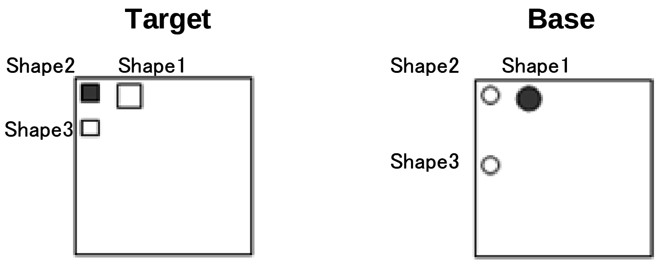
Surface similarity is calculated through a process that is slightly modified from the one proposed by Forbus, Gentner, and Law [2]. The process is outlined in Figure 6, which shows two graphics, one of which was already shown in Figure 5. In this explanation, the graphic shown in Figure 5 is considered the target and the other is considered the base.

The process begins with the counting of the types of attributes in the representations. Figure 6 shows the representations of the base and the target. The results of the counting are listed in the table at the bottom of this figure.

The surface similarity is quantified as the dot product of two vectors that contain the frequencies of the attributes as elements. For the case of Figure 6, the score is a 17.

As indicated in the above explanation, the surface similarity score is calculated by a computationally cheap process. The score does not reflect a relational structure but reflects the frequencies of object attributes. Psychological studies have indicated that this kind of score is positively correlated with retrievability measured in studies of the human memory system [7, 12].

DRAFT



Target	Base
(2x Shape1)	(2x Shape1)
(1y Shape1)	(1y Shape1)
(4size Shape1)	(Oval Shape1)
(5darkness Shape1)	(4size Shape1)
(Rectangle Shape1)	(1darkness Shape1)
(1x Shape2)	(1x Shape2)
(1y Shape2)	(1y Shape2)
(1size Shape2)	(Oval Shape2)
(1darkness Shape2)	(1size Shape2)
(Rectangle Shape2)	(5darkness Shape2)
(1x Shape3)	(1x Shape3)
(2y Shape3)	(3y Shape3)
(1size Shape3)	(Oval Shape3)
(5darkness Shape3)	(1size Shape3)
(Rectangle Shape3)	(5darkness Shape3)

	1x	2x	1y	2y	3y	1size	4size	1darkness	5darkness	Rectangle	Oval
Target	2	1	2	1	0	2	1	1	2	3	0
Base	2	1	2	0	1	2	1	1	2	0	3

Figure 6: Calculations of surface similarity.

Structural similarity

Structural similarity is quantified as the size of relational structures common to the base and the target. The commonality of their relational structure is calculated by estimating the maximum mapping from the base to the target. The mapping process is guided by the following structural consistency constraints [10].

- Parallel connectivity
  If two predicates are placed into correspondence then the arguments to these predicates are also placed into correspondence, and vice versa.
- One-to-one mapping
  Each item in the base maps to at most one item in the target, and vice versa.

Several computational models that compute the score of structural similarity have been proposed in earlier studies in cognitive science. The most influential is the structure-mapping engine (SME) [1]. The model receives two descriptions (the base and the target), then searches the maximum mapping from the base to the target. Although the mapping process is constrained by the structural consistency, it is exhaustive. It searches for every possible mapping from the base to the target. After that, the model selects the biggest one from all the resulting mappings and estimates the score of the structural similarity. The SME is considered a domain-general model for analogical reasoning and has therefore been applied to many tasks, including story comprehension [12], problem solving in physics [4], and diagrammatic reasoning [11, 15].
It has been pointed out, however, that there are computational limitations in the SME algorithms. Since the number of mappings increases dramatically with the number of propositions in the domains, it cannot be applied to complex visual domains where thousands of features are involved. Models intended to reduce the computational costs of mapping have therefore been proposed [3, 8]. These models do not search for all the possible mappings but selectively search for only a few. Incremental

Analogical Mapper (IAM) [8], for example, finds the deepest element in the base structure and then searches from that element for a consistent mapping to the target.

These methods cannot be applied to our task, however, because our representations are developed in the bottom-up manner and there is no deepest element in our representation. We therefore modified the algorithms in previous models and developed a model with the following three stages.

1. P-match Construction:

The model first constructs the correspondences of propositions. These correspondences (P-matches) are created by comparing the predicates in the base proposition with the predicates in the target proposition. If the two propositions have a predicate that is the same, a P-match is created.

Each of the P-matches consists of a pair of predicates (a Pre-match) and pairs of augments (O-matches). For example, if the base contains the proposition *(vertical Shape1 Shape3)* and the target contain the proposition *(vertical Shape3 Shape3),* the following P-match is created.

((vertical vertical) (Shape1 Shape2) (Shape3 Shape3))

This process is applied to every possible combination of propositions, and a list that contains every constructed P-match is created.

2. Determine a starting-point:

To sort the list of P-matches, the model assigns the following weights to each P-match in the list.

- O-match frequencies
  This weight reflects the frequencies of the O-matches in the list of P-matches. This is calculated as a summation of the individual O-match frequency (*freq (O-matchi), freq(O-matchj)*) and co-occurrence frequency (*freq (O-matchi, O-matchj)*).
- Pre-match frequencies
  This weight reflects the dimensions (e.g., distance, density, size) of the Pre-match. The number of occurrences of each dimension is counted from the entire P-match list. Then the P-match is assigned the number of corresponding dimensions as the weight.

These weights can be considered the relevancies of the learner's focus. It can be assumed that in the composition task, a learner would focus on specific sets of objects or dimensions. This assumption is consistent with psychological findings. Spencer-Smith and Goldstone report that human subjects tend to estimate higher similarity when the mapping is concentrated on specific objects or dimensions [13].

3. Global map construction

In the third stage, the model constructs a global map that is a set of consistent P-matches. The basis for this process is an investigation of whether a pair of P-matches conflict with each other. Conflicts are defined as situations where several P-matches share the same object but differ from one another. Beginning with the top of the sorted list, the model sequentially chooses one of the P-matches and deletes the P-matches conflicting with it. The process results in a set of consistent P-matches.

The global mapping process is illustrated schematically in Figure 7, where descriptions are represented as propositional networks. The networks in the top and middle parts of Figure 7 represent the base and the target structures constructed from the graphics in Figure 6. The oval nodes represent predicates, and the boxed nodes represent objects. There are two types of links, solid links connecting a predicate with its first augment and dashed links connecting a predicate with its second augment. If the predicate is commutative, there are no distinctions between these two types of links.

The bottom network in the figure represents a global map from the base to the target. It does not contain pairs of predicates whose types are different or pairs of predicates whose augments are not placed in corresponding positions.

The structural similarity score is the number of elements in the global map. In Figure 7, the score is a 13. A past psychological study indicated that this kind of score is positively correlated with human ratings of “analogical soundness” [7, 12].

DRAFT

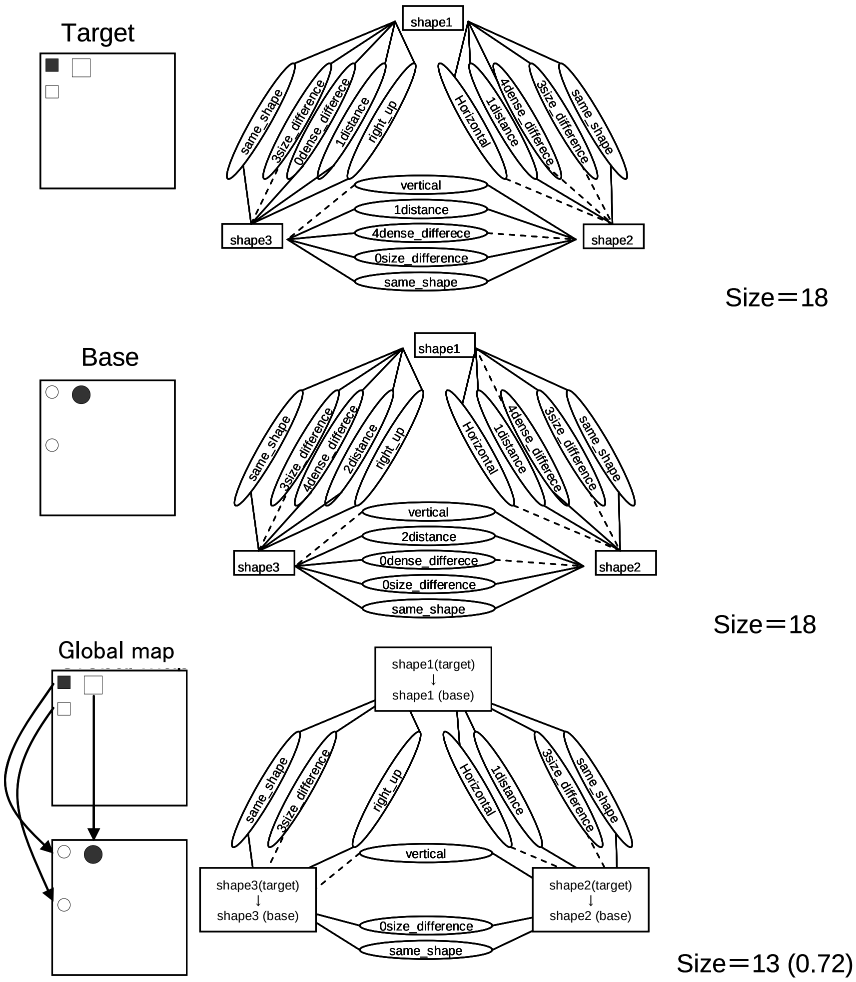


Figure 7: Example of global mapping.

4. EXPERIMENT

4.1 Aims

We evaluate the model by investigating the correspondence between human ratings and the scores calculated by the model.

4.2 Method

Participants

Sixteen subjects participated in the experiment.

Materials

The materials used in this experiment were created in such a way as to avoid any bias in the sampling. We first prepared ten graphics containing five objects whose attributes were assigned randomly and then combined those graphics into 45 pairs.

Procedures

Each participant intuitively rated the similarity of the two graphics in two or three pairs of graphics.

4.3 Results and Discussion

Four pairs of graphics were excluded from the following analysis because of failures in the experimental procedures. The surface and structural similarity scores for the other 41 pairs were calculated by the model presented in Section 3. The results are shown in Figure 8. The cells in the figure indicate the 45 pairs of the random graphics. Each of them contains three values. The value in the top indicates the mean evaluation scores for each graphic pairs. The values in the middle and low represent the surface and structural similarity scores for each graphic pairs.

The scores calculated by the model were evaluated by using Pearson's correlation coefficient with human ratings of similarity. As a result, a significant positive correlation was found only for correlation between the rating scores and the scores of surface similarity: $r = 0.40$, $p < .01$. The correlation between the rating scores and the scores of structural similarity did not reach a significant level: $r = 0.10$, *n.s.* These results indicate that the rating scores of similarity are influenced more by the surface similarity between the graphics than by the structural similarity between them. This interpretation is consistent with our hypothesis presented in Section 2. The results, however, do not show validity of structural similarity, so further evaluations of the model are required.

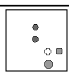
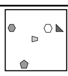
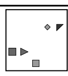
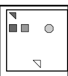
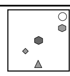
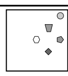
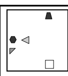
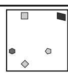
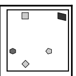
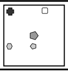
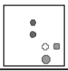
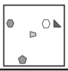
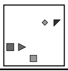
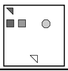
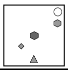
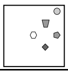
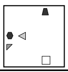
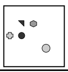
									
	2 0.62 0.40	3 0.53 0.38	1 0.42 0.36	2 0.38 0.32	2 0.52 0.40	2 0.64 0.46	4 0.43 0.40	3 0.51 0.38	4 0.72 0.40
		3 0.58 0.48	1 0.61 0.46	1 0.43 0.36	4 0.64 0.42	1 0.49 0.40	3 0.57 0.48		1 0.47 0.32
			4 0.62 0.42		4 0.76 0.46	3 0.57 0.46		3 0.56 0.38	4 0.49 0.30
					3.5 0.63 0.52	4 0.62 0.44	2 0.62 0.42	2 0.56 0.40	3 0.57 0.44
					1 0.51 0.40	1 0.55 0.50	3 0.44 0.38	2 0.48 0.50	1 0.48 0.36
						3 0.48 0.36	4 0.58 0.42	2 0.45 0.44	2 0.48 0.48
							2 0.63 0.38	2 0.72 0.46	3 0.66 0.40
								2 0.66 0.42	1 0.48 0.48
									1 0.48 0.32

Figure 8: Results of the experiment.

5. IMPLICATIONS AND FUTURE STUDIES

Our system is an application of the model of analogical reasoning. There have been many attempts to implement that model in a design support system [4, 9, 14], and most of them have used it to retrieve examples from a database. In the system proposed by Forbus et al. [4], for example, the model receives a designer's design solution and then retrieves examples from the database. The designer receives the matching results and inference produced by the model.

Our study can be distinguished from the past studies because our system does not retrieve examples. Instead it computes the two scores for the similarity between a presented example and a work created by a learner. The scores are used to evaluate the learner's perspectives on the example. While we think that these similarity scores could be used to prompt a learner's reflective thinking, this paper does not provide any evidence that such feedback has any effect on learning. This must be investigated in future studies. We must also carefully consider the learning goal, shifting a leaner's perspectives from surface features to structure features. This shift may be effective in the early stages of learning but insufficient for cultivating creativity. In the later stages of learning, it might be necessary to cultivate an ability to discover a variety of structures in the example. A system supporting design learning should therefore shift the learner's perspective not only to the biggest structure in an example but also to the varieties of structures in the example.

6. CONCLUSION

In this paper we presented two hypotheses about how people learn to compose consistent figures and introduced a learning support system that uses an analogical reasoning model. We also reported experimental results demonstrating the validity of that model. In the future we will evaluate the system in more detail.

REFERENCES

[1] Falkenhainer, B., Forbus, K. and Gentner, D., The Structure-Mapping Engine: Algorithm and example. *Artificial Intelligence*, 1989, 41, 1–63.

[2] Forbus, K., Gentner, D. and Law, K., MAC/FAC: A model of similarity-based retrieval. *Cognitive Science*, 1995, 19, 141–205.

[3] Forbus, K. D. and Oblinger, D., Making SME greedy and pragmatic. In *12th Annual Conference of the Cognitive Science Society*, Cambridge Mass, July 1990, pp.61–68 (Lawrence Erlbaum Associates).

[4] Forbus, K., Whalley, P., Everett, J., Ureel, L., Baher, J. and Kuehne, S., CyclePad: An articulate virtual laboratory for engineering thermodynamics. *Artificial Intelligence*, 1999, 114, 297–347.

[5] Holyoak, K. J. and Thagard, P., Analogical mapping by constraint satisfaction. *Cognitive Science*, 1989, 13, 295–355.

[6] Gentner, D., A theoretical framework for analogy. *Cognitive Science*, 1983, 7, 155–170.

[7] Gentner, D., Rattermann, M. and Forbus, K., The role of similarity in transfer: Separating retrievability for inferential soundness. *Cognitive Psychology*, 1993, 25, 524–575.

[8] Keane, M. T., Ledgeway, T. and Duff, S., Constraints on analogical mapping: A comparison of three models. *Cognitive Science*, 1994, 18, 387–438.

[9] Kulinski, J. and Gero, J. S., Constructive representation in situated analogy in design. In *Proceedings of the 9th International Conference on Computer Aided Architectural Design Futures*, 2001, pp.507–520 (Kluwer Academic Publishers, Dordrecht).

[10] Larkin, J. H. and Simon, H. A., Why a diagram is (sometimes) worth 10,000 word. *Cognitive Science*, 1987, 11, 65–99.

[11] Markman, A. B. and Gentner, D. Structural alignment during similarity comparisons. *Cognitive Psychology*, 1993, 25, 431–467.

[12] Morita, J. and Miwa, K., A Computational Analysis Model for Complex Open-ended Analogical Retrieval. In *6th International Conference on Cognitive Modeling*, ICCM ’04, Pittsburgh, July 2004, pp.202–207 (Lawrence Erlbaum Associates).

[13] Spencer-Smith, J. and Goldstone, R. L. The dynamics of similarity. *Bulletin of the Japanese Cognitive Science Society*, 1997, 4, 38–56.

[14] Takeda, H., Sasaki, H., Nomaguchi, Y. Yoshioka M., Shimomura, Y. and Tomiyama, T. Universal Abduction Studio – Proposal of a Design Support Environment for Creative Thinking in Design. in *International Conference on Engineering Design, ICED ’03,* Stockholm, August 2003,

[15] Tomai, T., Lovett, A., Forbus, K., and Usher, J., A Structure Mapping Model for Solving Geometric Analogy Problems. in *27th Annual Conference of the Cognitive Science Society*, Stresa, July 2005, pp.2190–2195 (Lawrence Erlbaum Associates).

Contact: Junya Morita
Japan Advanced Institute of Science and Technology
School of Knowledge Science
1-1 Asahidai
923-1292, Nomi, Ishikawa
Japan
Tel. +81-761-51-1707
Fax. +81-761-51-1149
e-mail. j-morita@jaist.ac.jp
URL. http://www.jaist.ac.jp/~j-morita/e-index.html