Towards the Evolution of a Language for Creative Design

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***Abstract*—In order to improve the creativity of computer aided design, a grounded artificial language with creative properties such as ambiguity and duality of patterning need to be developed. Initially, before using artificial language for creative design, the possibility of transforming between artificial utterances and design concepts should be tested. In this paper, a hybrid system including Holographic Reduced Representations (HRR) and Self-Organizing Map (SOM) is built up to represent spatial relations of simple shapes, and develop mapping between the representations and relevant artificial utterances. The computational results have proved that the transformation between artificial language and design concepts can be realized; and the hybrid system could be utilized as an important part of the "brains" of curious agents for the evolution of artificial language in computational language games.**

I. Introduction

Language plays many important roles in design from the specification of requirements to the collaboration between design team members, and the documentation of designs. I.e., language is not only important for communication between clients and designers, but also useful for creating concepts and transmitting knowledge to stimulate creative design. By utilizing design language, semantic labels for design concepts would be produced to allow "thinking by writing" in ways similar to "thinking by sketching".

A. The language of design

Generally, as Dong (2009) stated, the language of design is mainly used for aggregating design elements related with association, and accumulating design structures relating to combination, as well as evaluating design works via the analysis of design concept with respect to goals. Among them, aggregation is very important for finding new concepts and transforming design ideas to some new areas. For example, an architect made a claim "the shape of the pavilion's roof resembles a leaf." Then the word-graph system displays a key phrase in the statement "leaf". Later, the architect might make another statement "I would like the building's structure to be organic, to remind the occupants of a plant". Then the system might display a semantically related term such as "flower" or "root". Therefore, design language could be utilized to improve design creativity [1]. In addition, Clark (1996) pointed out that language is the "ultimate artefact" whose primary purpose is not to communicate ideas between individuals but to overcome cognitive limitations of the human brain through the externalisation of complex thought in a grounded symbolic form [2].

Particularly, Language can be utilized to generate new concepts via connection. Hori (1994) developed a system which may reveal hidden relations that were not easily noticed by the user, who only needs to provide some basic symbols and part of relations. In this system, the distance of conceptual connection is measured by using multidimensional scaling method. For example, if a word "A", which has no relation with "C", has relation with "B". The distance between "A" and "B" is smaller than that of "A" and "C". In addition, a word "D" may come near "A", when "A" has some relation with "B" and "B" has relation with "D". This may surprise the user who is unaware of the relation between "A" and "D". Furthermore, the existing words are mapped into Euclidean space which can be taken as a stimulus for detecting empty place, relation, aggregation and exchange of nodes [3].

As described above, novel concepts could be found by connecting different words. Accordingly, the transformation from design requirements to functions, which is at the beginning of creative design process (Function-Behavior-Structure [4]), may probably be realized and enriched by utilizing compositional language. Requirements are related with design problems while functions are associated with design concepts. The transformation from design problems to design concepts could be realized by combining symbolic representations and visual illustrations. In addition, compositional language can evolve during the communication between clients and designers to refresh and refine design concepts. Consequently, evolutionary design may occur via the helix circulation of problem finding and problem solution aided by connecting various utterances representing different design concepts.

B. The Evolution of Language

Language is a distributed and self organizing system evolving in social communication, from simple utterances generated by combination and transformation to complex emergence via composition, decomposition and recursion etc. Through evolution, a shared lexicon of words and their associated meanings would be generated [5]. The evolution of grounded language for creative design may start from distributing symbolic units randomly. Then various utterances would evolve to represent different design concepts, which could be connected to adapt surroundings to embodied design requirements.

The prime properties of languages for creative design are ambiguity and duality of patterning such that a small stock of meaningless sounds can be combined in numerous permutations to make up a very large number of meaningful units [6]. As is known, a single word may have multiple meanings and different words may have similar meaning. In addition, familiar words might have unfamiliar meanings. Even when two people say the same word, it may denote different meanings in terms of various contexts. Although ambiguity sometimes may lead to misunderstanding, it can become the source of creativity related with diversity. Some of our previous multi-agent experiments have shown that, the variety of meanings held by a field for a single word increases highly as a consequence of individuals searching for novel topics. Particularly, the ambiguities that arise in domain-specific languages are evolved from the perspective of modeling these languages [5].

For the evolution of language, Steels (1995) utilized language games to evolve artificial utterances in multi-agent systems. One of these language games is guessing game, in which one agent, the initiator, describes an object using a simple utterance to a second agent, the recipient, who attempts to identify the topic of the utterance based on their experience of the previous utterances. Steels has shown that repeated playing of such language games is capable of evolving languages grounded in shared experiences [7].

Based on Steels' general language games, more complicated language games for creative design could be simulated with the aid of associative representations representing multiple relations of design shapes. Our experiments here are trying to use appropriate representations to represent complex relations of shapes and exploring new design concepts via artificial neural networks. To simplify these experiments, geometric relations between two rectangles (see Fig. 1) are chosen as subjects, which could be extended to Rectilinear Volumes [8] in future simulations.

II. HYBRID SYSTEM

Geometrical relations can not only be represented by utilizing associative representations but also be explored and enriched via machine learning to match generated "utterances" with appropriate relations, and find new spatial relationships. I.e., the transformation between design concepts and artificial languages can be realized by adopting hybrid system combining symbolic components and artificial neural networks [9]. The hybrid system used here is the integration of Holographic Reduced Representations (HRR) [10] and Self-Organizing Map (SOM) [11], which has been used successfully by Levy and Kirby (2006) in their experiment for developing regular mappings between meanings and sequences [12]. Consequently, the hybrid system would become an important part of the "brains" of curious agents running in multi-agent environment to develop artificial language such as artificial

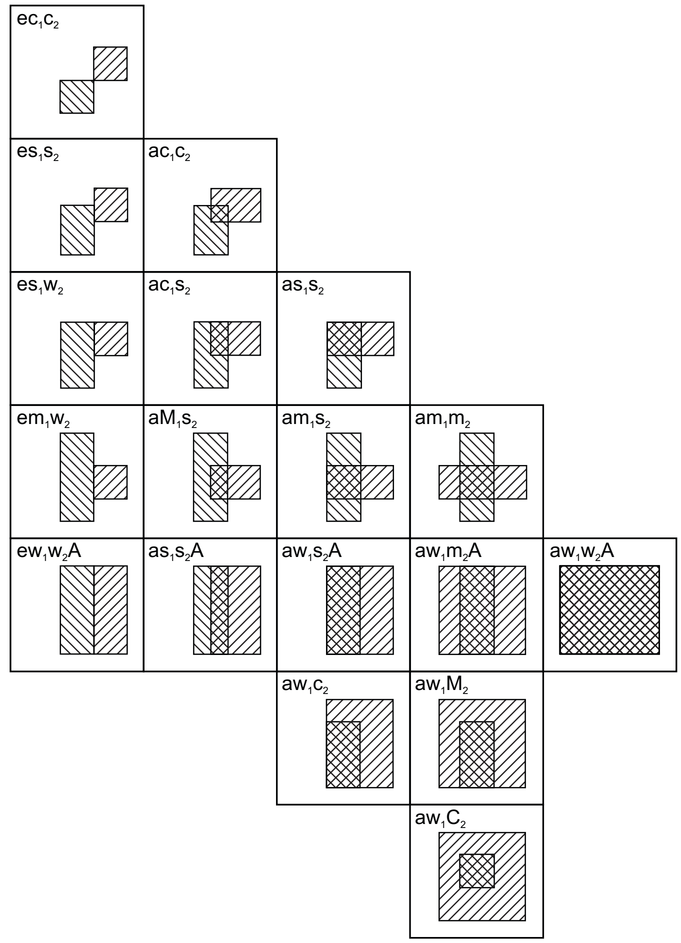


Fig. 1. The relations between two rectangles

"utterances" for creative design based on Domain-Individual-Field-Interaction framework [13].

A. Holographic Reduced Representations

Holographic Reduced Representations (HRR) are capable of refreshing relative concepts and organizing the clusters of ideas, and using memory efficiently for distributed representations. By using HRR, reasonable representations could be generated through the combination of basic rules and randomness. In addition, the similarity between different geometric relations can be measured by using cosine. Further, complicated relations can be represented within the same space of memory as that of simple relations [10].

A language may evolve as a tree-like structure via composition and decomposition within Holographic Reduced Representations (HRR). High-level combination can be produced by combining several words from different linguistic trees such as the combination of "fly" and "fish" to generate innovative concepts. At the same time, complex design concepts can be decomposed into embodied elements by tracking their associations and categories. HRR (see Fig. 2)can realize both of them by using circular convolution ($t = c \otimes x$, see Equation (1) and Algorithm 1) composing items, and circular correlation

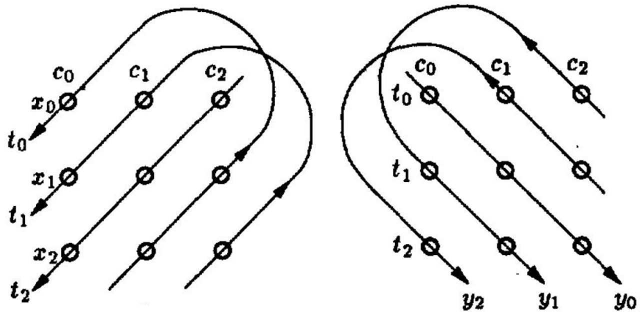


Fig. 2. Circular convolution and circular correlation [10]

($y = c \oslash t$, see Equation (2) and Algorithm 2) decoding convolution. Therefore, complicated symbolic system could be encoded and decoded by using HRR[10].

$$t_j = \sum_{k=0}^{n-1} c_k x_{j-k} \tag{1}$$

for $j = 0$ to $(n-1)$ (Subscripts are modulo-n)

Algorithm 1 Circular convolution $t = c \otimes x$

$c \leftarrow self.value$; $x \leftarrow other.value$; $t \leftarrow emptyList$
for $j = 1 \rightarrow self.dimensions$ **do**
  $t \leftarrow t + None$
  $t[-1] \leftarrow 0$
  for $k = 1 \rightarrow self.dimensions$ **do**
    $i \leftarrow (j-k+self.dimensions) \ mod \ self.dimensions$
    $t[j] \leftarrow t[j] + c[k] * x[i]$
  end for
end for

$$y_j = \sum_{k=0}^{n-1} c_k t_{j+k} \tag{2}$$

for $j = 0$ to $(n-1)$ (Subscripts are modulo-n)

Algorithm 2 Circular correlation $y = c \oslash t$

$c \leftarrow self.value$; $t \leftarrow other.value$; $y \leftarrow emptyList$
for $j = 1 \rightarrow self.dimensions$ **do**
  $y \leftarrow y + None$
  $y[-1] \leftarrow 0$
  for $k = 1 \rightarrow self.dimensions$ **do**
    $i \leftarrow (j+k) \ mod \ self.dimensions$
    $y[j] \leftarrow y[j] + c[k] * t[i]$
  end for
end for

To evaluate the quality of Holographic Reduced Representations (HRR), some general measurement methods such as cosine similarity need to be adopted. As is known, the cosine of zero is one, which means the two vectors are the same. If it is less than one, they are different. When the cosine becomes smaller, the difference between them becomes greater. Therefore the cosine of the angle between two vectors can be utilized to measure the similarity between geometric relations represented via HRR[14].

B. Self-Organizing Map

Self-Organizing Map (SOM), which is an unsupervised competitive learning method, is used to develop the mapping between the distributed representations of symbolic sequences and the distributed representations of propositions. Both symbolic sequences and propositional meanings are represented by high dimensional vectors of real numbers generated via HRR [12]. These vectors include both the vectors representing different meanings of rectangular relations and the vectors representing relevant "utterances" taken as nodes for SOM. Meaning-vectors and symbolic-vectors could be matched by using Self-Organizing Map (SOM). After a number of generations, the network would develop systematically regular mapping between meanings and "utterances" [12].

III. Experiments and Results

In our computational experiments, the relative relations of two rectangles (see Fig. 1) have been categorized via Holographic Reduced Representations (HRR) successfully. Following HRR, the representations of rectangular relations were taken as initial samples for running Self-Organizing Map (SOM) to match numbers of "utterances" with these representations.

A. Representing the relations between two rectangles

The relative relations between two rectangles are defined by three features. They consist of the types of geometry including edge and area shared by two rectangles; different parts including corner, side, middle, mid-side, center and whole of share with them (see Table I); and the axis absolutely shared by some rectangular relations (see Fig. 3). To begin with, each general feature such as shape, share-geometry, share-part and share-axis is represented as a random vector with 1024 (32x32) dimensions (see Table II and Fig. 4). Secondly, detailed elements are generated via addition or circular convolution with these general features (see Table III and Fig. 4). Then, eighteen rectangular relations are represented by combining these elements via addition and circular convolution of HRR (see Table IV).

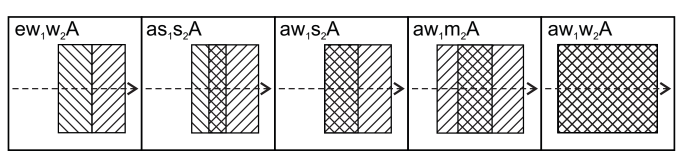


Fig. 3. Share axis

Each name of these rectangular relations is generated with three or four characters. The first character is chosen between "e" and "a"; "e" means two rectangles share at least part of edge while "a" means they share at least part of area. The

TABLE I
CATALOG OF SHARING EDGE AND AREA

share	share edge			share area					
whole	es$_1$w$_2$	em$_1$w$_2$	ew$_1$w$_2$A	aw$_1$s$_2$A	aw$_1$m$_2$A	aw$_1$w$_2$A	aw$_1$c$_2$	aw$_1$M$_2$	aw$_1$C$_2$
side	es$_1$s$_2$	es$_1$w$_2$		ac$_1$s$_2$	as$_1$s$_2$	aM$_1$s$_2$	am$_1$s$_2$	as$_1$s$_2$A	aw$_1$s$_2$A
corner	ec$_1$c$_2$			ac$_1$c$_2$	ac$_1$s$_2$	aw$_1$c$_2$			
middle	em$_1$w$_2$			am$_1$s$_2$	am$_1$m$_2$	aw$_1$m$_2$A			
mid-side				aM$_1$s$_2$	aw$_1$M$_2$				
center				aw$_1$C$_2$					

TABLE II
HRR OF GENERAL FEATURES OF RECTANGULAR RELATIONS

$shape = HRR(\text{“}shape\text{”}, random())$
$shareGeometry = HRR(\text{“}geometry\text{”}, random())$
$sharePart = HRR(\text{“}part\text{”}, random())$
$shareAxis = HRR(\text{“}axis\text{”}, random())$

second and third character are selected from “c”, “s”, “m”, “M”, “C” and “w”. “c” means corner; “s” means side; “m” means middle; “M”, which means partial middle (mid-side), is only for sharing area (see the vertical brick of “aM$_1$s$_2$” compared with that of “am$_1$s$_2$” at the center of Fig. 1); “C” means center; and “w” means whole. For examples, “aw$_1$C$_2$” means one rectangle share its whole area while another one only share its center (see the bottom relation in Fig. 1); “ec$_1$c$_2$” means the two shapes both share a “corner” of their edges while “ac$_1$c$_2$” means the two shapes both share a corner of their areas (see the top relations in Fig. 1). In addition, some names have the forth character, “A”, which means two rectangles share at least one axis regardless of the change of their sizes or that of the ratio of width to height (see Fig. 3). In Table IV, “axis(0)” means it is not essential to share axis,

TABLE III
HRR OF DETAILED ELEMENTS OF RECTANGULAR RELATIONS

shape	$shape_1 = shape + HRR(\text{“}shape1\text{”}, random())$ $shape_2 = shape + HRR(\text{“}shape2\text{”}, random())$
share Geometry	$edge = shareGeometry \otimes HRR(\text{“}edge\text{”}, random())$ $area = shareGeometry \otimes HRR(\text{“}area\text{”}, random())$
sharePart	$corner = sharePart \otimes HRR(\text{“}corner\text{”}, random())$ $side = sharePart \otimes HRR(\text{“}side\text{”}, random())$ $middle = sharePart \otimes HRR(\text{“}middle\text{”}, random())$ $midside = sharePart \otimes HRR(\text{“}midSide\text{”}, random())$ $center = sharePart \otimes HRR(\text{“}center\text{”}, random())$ $whole = sharePart \otimes HRR(\text{“}whole\text{”}, random())$
shareAxis	$axis(0) = shareAxis \otimes HRR(\text{“}axis(off)\text{”}, random())$ $axis(1) = shareAxis \otimes HRR(\text{“}axis(on)\text{”}, random())$

TABLE IV
HRR OF THE RELATIONS BETWEEN TWO RECTANGLES

$ec_1c_2 = (edge + shape_1 \otimes corner + shape_2 \otimes corner) + axis(0)$
$es_1s_2 = (edge + shape_1 \otimes side + shape_2 \otimes side) + axis(0)$
$ac_1c_2 = (area + shape_1 \otimes corner + shape_2 \otimes corner) + axis(0)$
$es_1w_2 = (edge + shape_1 \otimes side + shape_2 \otimes whole) + axis(0)$
$ac_1s_2 = (area + shape_1 \otimes corner + shape_2 \otimes side) + axis(0)$
$as_1s_2 = (area + shape_1 \otimes side + shape_2 \otimes side) + axis(0)$
$em_1w_2 = (edge + shape_1 \otimes middle + shape_2 \otimes whole) + axis(0)$
$aM_1s_2 = (area + shape_1 \otimes midside + shape_2 \otimes side) + axis(0)$
$am_1s_2 = (area + shape_1 \otimes middle + shape_2 \otimes side) + axis(0)$
$am_1m_2 = (area + shape_1 \otimes middle + shape_2 \otimes middle) + axis(0)$
$ew_1w_2A = (edge + shape_1 \otimes whole + shape_2 \otimes whole) + axis(1)$
$as_1s_2A = (area + shape_1 \otimes side + shape_2 \otimes side) + axis(1)$
$aw_1s_2A = (area + shape_1 \otimes whole + shape_2 \otimes side) + axis(1)$
$aw_1m_2A = (area + shape_1 \otimes whole + shape_2 \otimes middle) + axis(1)$
$aw_1w_2A = (area + shape_1 \otimes whole + shape_2 \otimes whole) + axis(1)$
$aw_1c_2 = (area + shape_1 \otimes whole + shape_2 \otimes corner) + axis(0)$
$aw_1M_2 = (area + shape_1 \otimes whole + shape_2 \otimes midside) + axis(0)$
$aw_1c_2 = (area + shape_1 \otimes whole + shape_2 \otimes center) + axis(0)$

or no axis is shared. On the contrary, “axis(1)” indicates that at least one axis should be shared.

To clarify the process of HRR for representing rectangular relations, a tree structure of the representation of relation named “ac$_1$s$_2$” is illustrated in Fig. 4. As can bee seen, the process consists of three steps. The first step is to generate general features shown on level 1. Each feature is represented by a list of random numbers with 32x32 dimensions. The second step is to produce elements shown on level 3 by combining relevant features and some new lists of random numbers shown on level 2. For example, “area” is generated by convoluting “shareGeometry” and a new list of random numbers named “area_”. This convolution and another convolution of “shareGeometry” and some other new list for “edge” can be used to clarify the relationships between “shareGeometry”, “area” and “edge”. Among them “area” and “edge” are two types of geometric share. In this example, area instead of only edge is shared between two rectangles. So “area” is selected to represent this relation. After generating all elements, the third step is to select appropriate elements and combine them into one list of numbers with the same dimensions. In this example, “corner” is combined with “shape1” to produce “corner1 (c$_1$)” while “side” is combined with “shape2” to generate “side2 (s$_2$)”. Then “corner1 (c$_1$)” and “side2 (s$_2$)” are combined with “area (a)” to generate a new list, which is combined with “axis(0)” to produce the final list named “ac$_1$s$_2$”. Here, “A” is not added into this name because two rectangles do not share axis (“axis(0)”) in this relation.

B. The results of representations

The results of HRR representations were clarified by using cosine similarity to analyse the difference between eighteen rectangular relations. The similarities of these relations are shown in Table V. The similarity between two relations is greater when the color is lighter. The difference between each other is clarified regarded with the range of similarities from 0.19 to 1.00 covering 81% of the whole possible distributed area. Therefore, the relations between two rectangles have

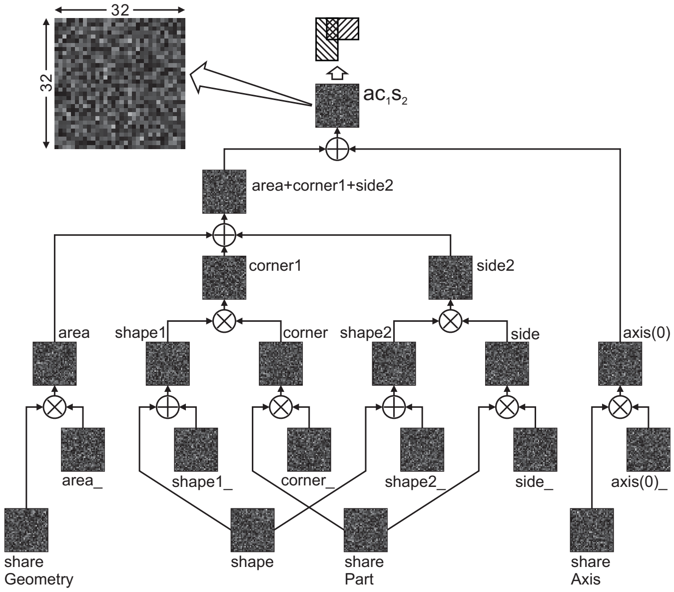
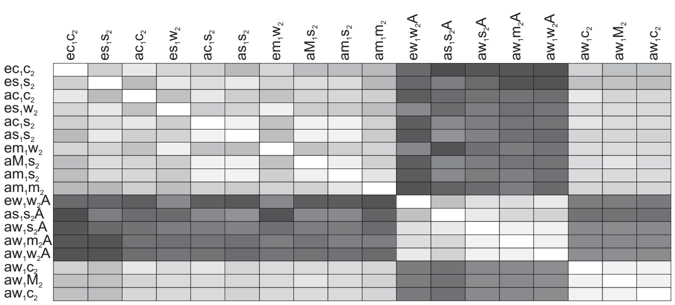


Fig. 4. Example of HRR process

TABLE V
COSINE SIMILARITIES BETWEEN RELATIONS OF TWO RECTANGLES



been distinguished clearly and successfully by utilizing HRR.

C. Mapping "utterances" to representations

The "utterances" for mapping are also generated via HRR (see Algorithm 3). Each node such as "fabeji" is composed of six elements selected from different sets including $set_1(b, c, d, f, g, h)$, $set_2(j, k)$, $set_3(a, e)$ and $set_4(i, o)$. By combining all of these elements ($6 \times 6 \times 2 \times 2 = 144$), one hundred forty-four nodes are generated for SOM to map the representations of eighteen rectangular relations.

In the process of mapping, forty nine epochs were implemented. Each epoch included four hundred iterations. As illustrated in Fig. 5, the process can be divided into three stages. The first stage is from epoch 1 to 17. In this stage, the mapping between relations and utterances was unstable in terms of extreme change of mapping from one epoch to another epoch. The average success rate was lower than 1.3%. In addition, an average of 16% of relations was not distinguished from others as shown with the degrees of difference. I.e., almost three relations were mapped with the same utterance in each epoch. In the second stage from epoch 18 to 26, the success rate increased sharply from 5.6% to 100%; and each relation was

Algorithm 3 Generate nodes for SOM

$set_1 \leftarrow list(\text{"}b\text{"}, \text{"}c\text{"}, \text{"}d\text{"}, \text{"}f\text{"}, \text{"}g\text{"}, \text{"}h\text{"})$
$set_2 \leftarrow list(\text{"}j\text{"}, \text{"}k\text{"})$
$set_3 \leftarrow list(\text{"}a\text{"}, \text{"}e\text{"})$
$set_4 \leftarrow list(\text{"}i\text{"}, \text{"}o\text{"})$
$nodes \leftarrow emptyList$
for $m = 1 \rightarrow set_1.length$ **do**
  for $n = 1 \rightarrow set_1.length$ **do**
    for $u = 1 \rightarrow set_2.length$ **do**
      for $v = 1 \rightarrow set_4.length$ **do**
        $newNodes \leftarrow set_1[m] \otimes set_3[0] + set_1[n] \otimes set_3[1] + set_2[u] + set_4[v]$
        $nodes \leftarrow nodes + newNodes$
      end for
    end for
  end for
end for

mapped to different utterance. The last stage is from epoch 27 to 49. In this stage, the mapping between relations and utterances became stable. No mapping was changed and each relation was mapped to final appropriate utterance.

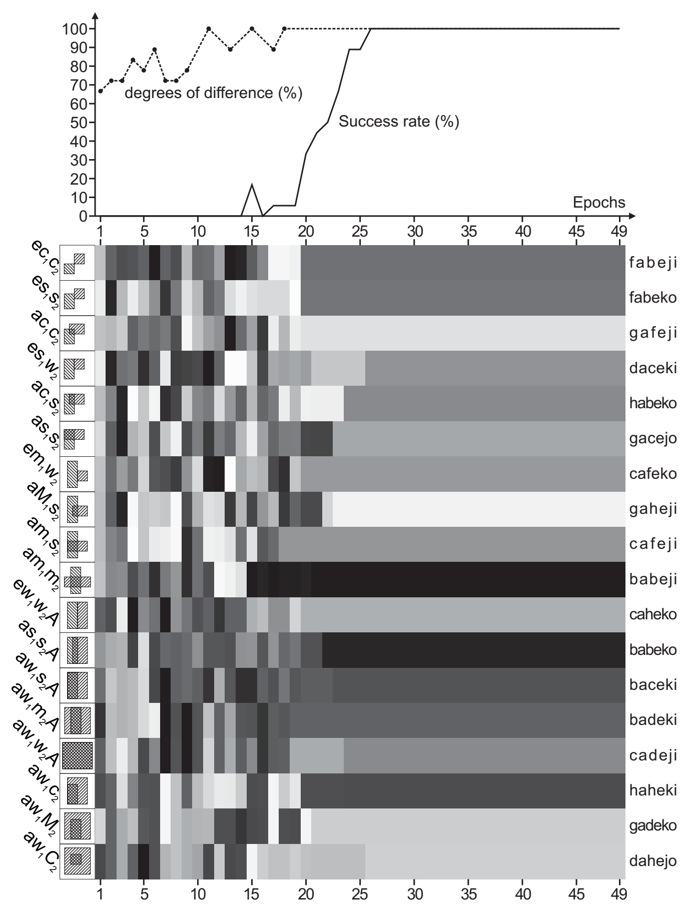


Fig. 5. The process of mapping "utterances" to representations

TABLE VI
THE NUMBER OF EPOCHS WHEN OBTAINING EACH FINAL RESULT

ec_1c_2	es_1s_2	ac_1c_2	es_1w_2	ac_1s_2	as_1s_2	em_1w_2	aM_1s_2	am_1s_2
fabeji	fabeko	gafeji	daceki	habeko	gacejo	cafeko	gaheji	cafeji
20/49	20/49	20/49	26/49	24/49	23/49	20/49	23/49	18/49
am_1m_2	ew_1w_2A	as_1s_2A	aw_1s_2A	aw_1m_2A	aw_1w_2A	aw_1c_2	aw_1M_2	aw_1c_2
babeji	caheko	babeko	baceki	badeki	cadeji	haheki	gadeko	dahejo
21/49	20/49	22/49	23/49	24/49	24/49	24/49	21/49	26/49

D. *The results of mapping*

Most results of mapping had been obtained before half of total epochs being executed (see Table VI). The average of epochs for obtaining results was 22 which made up 45% of the total epochs. In addition, different utterance was mapped to each relation after the 18th epoch which was in the early stage occurring 37% of the total epochs. Therefore, SOM was implemented efficiently and successfully.

IV. DISCUSSION AND FUTURE WORK

The mappings between rectangular relations and artificial utterances have been completed by using the hybrid system integrating Holographic Reduced Representations (HRR) and Self-Organizing Map (SOM). The success is mainly due to the compact and clear structure of the HRR of both geometric relations and nodes used in SOM. For the former, each relation is represented by two circular convolutions and three additions (see Table IV), while for the latter, each node is generated with similar structure as that of the former; and the total of nodes is 144, which is enough for matching appropriate nodes labelled with utterances to the eighteen relative relations of two rectangles. In brief, the results of this experiment have proved the possibility of transforming between artificial languages and design concepts completed via the hybrid system within associative memories and artificial neural networks.

The experiment implemented here is emphasized on the transformation from "utterances" to existing design knowledge. In future, new "utterances" would be generated by recombining existing symbolic elements, and be transformed to new design concepts which may be some missing design parts relating to uncovered field. In addition, instead of Self-Organizing Map, some other machine learning methods such as Boosting [15], which includes iteratively learning weak classifiers with respect to a distribution and adding them to a final strong classifier, would be adopted to improve the performance of transformation between design knowledge and artificial language for creative designing.

Further, relevant simulations for evolving design language will be implemented in multi-agent environment via the interaction between different curious agents and cultures. For example, the guessing game played by speaker agent and listener agent will be simulated to develop an artificial language for shape design. In each epoch of this game, speaker chooses one relation between two rectangles, perceives it and generates an utterance representing the relation, then shares the utterance with listener. Listener receives the utterance, compares it with existing utterances, maps it to suitable relation, and shows the relation to speaker. Then, speaker would agree or disagree with listener. Via repeatedly interaction between speaker transforming ontology to lexicon and listener transforming lexicon to ontology, a shared language accepted by both of them would be developed for generating and exchanging "interesting" works with associated utterances [5]. Consequently, novel design concepts would be generated due to the creative properties of language, such as ambiguity and duality of patterning. As an expected result, a compositional artificial grounded language would evolve to support creative design.

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