ASSESSING CONCEPT NOVELTY POTENTIAL WITH LEXICAL AND DISTRIBUTIONAL WORD SIMILARITY FOR INNOVATIVE DESIGN

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ABSTRACT

Generating novel design concepts is a cornerstone for producing innovative products. Although many methods have been proposed for supporting the task, their performance depends on human ability. The goal of this research is to build a method supporting designers to generate novel design concepts with the knowledge of what factors have positive effects on the novelty. Toward the goal, this research assumes that the more distant two function concepts chosen, the more novel idea would come up with by the combination of the two concepts. Based on the assumption, this paper introduces a notion of novelty potential of the combination of two function concepts, and proposes a method to assess it by the function similarity. It is calculated with the integration of a lexical database for natural language called WordNet and a distributional semantics method called word2vec. The proposed method is adapted to case studies in which students perform design concept generation for given design tasks. The correlation analysis is performed to verify the assessment performance of the proposed method. This paper discusses its possibility based on the results of the case studies.

Keywords: Conceptual design, Creativity, Early design phases, Design methods, Word similarity

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1 INTRODUCTION

Manufacturing companies aiming at new product development contend with design problems which requires many kind of innovations that range from new-to-the-world ones to relatively simple improvements or adaptations (De Brentani, 2001). Generating novel design concepts in the conceptual design phase is a cornerstone for producing innovative products, because exploring various unconventional solution candidates in the early phase of product development process would give designed products the potential to be competitive in the market.

Brainstorming is one of the most well-known techniques for generating novel concepts due to its simple and easy to learn nature (Daly *et al*., 2016), while it is not a systematic method and it heavily depends on a designer's ability. Researchers in design engineering domain have built theories to understand the process of design concept generation (Hatchuel and Weil, 2009), and the indicators to assess its creativity (Ranjan *et al*., 2018). General Design Theory (GDT) (Yoshikawa, 1981) is a pioneering research of design process. It models design process as concept operations, i.e., set operational processes regarding the entity set and its subsets, and mathematically derives some theorems of designer's thinking process. One of findings of GDT is that a classification system of generated concepts takes an important role to help designers think logically and create new concepts. While those prior works would give us fundamental knowledge, there are not established methodologies to support design concept generation in a systematic way.

The ultimate goal of this research is to build a method supporting designers to generate novel design concepts with the knowledge of what factors have positive effects on the novelty. This research assumes that the more distant two concepts chosen, the more novel idea would come up with by the combination of the two concepts. It is referring the GDT framework of refining design concept space and finding new combination of concepts. Based on the assumption, this paper proposes a method to assess the novelty potential of the combination of two function concepts by the similarity between concepts based on the word similarity, and discusses its possibility to help designers find a novel idea. It is calculated with the integration of a lexical database for natural language called WordNet (Miller, 1995) and a distributional semantics method called word2vec (Mikolov *et al*., 2013) which is a neural network for processing corpus.

The novelty of this research is to introduce a notion of the novelty potential of design process, and to aim at assessing it with the data science technology for natural language processing, which will be a plausible approach for establishing a scientific method of design concept generation. This paper discusses its possibility based on the case study that the proposed method is adapted to design experiments in which students performs design concept generation for a given design task.

2 THEORETICAL BACKGROUNDS AND OUR APPROACHES

2.1 Prior works of design concept generation

The prior works of design concept generation can be roughly classified into two approaches, i.e., an empirical approach and a theoretical approach. An empirical approach is based on a practical study of design concept generation processes, and extracts some patterns of thought which work as knowledge to support designers. TRIZ is a well-known technique of this approach (Altshuller, 2005). It is based on the analysis of 2.5 million patents and the formalization of them into some patterns of thinking process. Han *et al*. (2018) developed a computational tool called "the Retriever" which has a knowledge database of patterns of analogical thinking. It can help designers produce creative ideas through design space expansion and exploration. A theoretical approach defines factors related to the creativity of designers' thinking process, then defines a prescriptive model of concept generation with those factors. There is a strong focus on measuring creativity and design outcomes (Fu *et al*., 2018). For example, Shah *et al.* (2003) defines the design creativity metrics of *novelty* and *variety*, which are calculated with a function tree made in design process, and *quantity* which is the number of ideas created in design process. Ranjan *et al*. (2018) defines the two major metrics of *novelty* and *usefulness* which are calculated by the degree of requirement-satisfaction. These assessment theories can be used to help designers think creatively during the design process.

Since the creativity relies on tacit thinking process of designers, both approaches inevitably depend on humans' ability when they are practically used, e.g., the adaptation of patterns to a real design problem

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in empirical approach, and the creativity assessment of actual designers' thinking process. Building a scientific theory which is independent from the humans' ability has been an open issue.

2.2 Concept generation theory based on GDT

GDT is a unique approach, as it is based on mathematical foundations of set theory to represent the concept space structure. It is an attempt to clarify the human ability of designing in a scientific way, and at the same time, producing the practical knowledge about design methodology (Yoshikawa, 1981). It can be a basis to explain design concept generation process scientifically.

The following simple anecdote shows the outline of concept operation framework assumed in GDT. Let us consider a primitive world, where only three kinds of meat are found, fresh meet, spoiled meet, and dried meet; all natural entities, without any artificial processing. As shown in Figure 1, people of the world recognized and memorized them as natural entities; $x_1 = \textit{fresh meat}$, $x_2 = \textit{spoiled meat}$, $x_3 = \textit{dry-bone meat}$. People in the world construct concepts about characteristics abstracted from these entities, which are called abstract concepts, giving classifications from the viewpoint of function or value of the entities. For example, let $T = \{T_1, T_2\}$ be a classification: $T_1 = \textit{changing with time}$, $T_2 = \textit{eatable}$ as shown in Figure 1. It is assumed that people had the ability of logical operations such as disjunction, conjunction, abstraction and classification. Someday, a person in the primitive world thought accidentally about; $\overline{T_1} \cap T_2 = \phi$. This combination leads to a defect of the classification, called void (Tomiyama *et al*., 2010). This had no correspondence to a real entity, but its characteristics "*eatable* and *not changing with time*" has higher value than the existing entities. This conceptual combination was the necessary condition to invent *smoked meat* (x_4), the first artificial entity for the human beings.

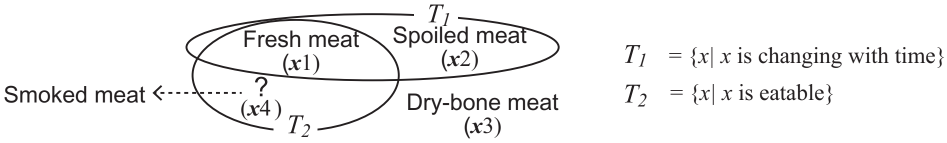

Figure 1. Example of design concept operation in GDT

The above simple anecdote implies that it is critical to have an image about specifications that have no immediate solutions. This is a necessary condition for creative design. The empty set in the classification system correspond to design solutions that never existed before.

Obviously, different classification can be made for the same initial entities. Let us take an example of the classification with *existing near/far from the habitation* and *smelling good/bad*. While the combination of those would lead to voids, it is easier to come up with entities corresponding to them, which are not novel. It is important to make the appropriate classification for exploring valuable novel concepts.

2.3 Our approaches

The prior works stated in Section 2.1 have a remaining issue that any theory and any assessment method depends on humans ability. While GDT stated in Section 2.2 has the possibility to give a scientific foundation of design concept generation theory, there is no guideline to make the classification leading to novel concepts. The authors assume that the more distant two concepts chosen, the more novel idea would come up with by the combination of the two concepts. According with prior works which focus on analogical distance and concept generation performance, the analogy from knowledge of farer field tends to lead to the more novel concepts (Chan *et al*., 2011; Taura and Nagai, 2013). They support the assumption of this research.

This research focuses on function as classification concept, because function concepts are effective to represent design information in conceptual design phase. Recent improvement of artificial intelligence technologies based on data science will increase the possibility to help process linguistic data more efficiently and objectively. This research employs them to measure the function similarity that must be a scientific scale to assess the novelty potential.

3 METHOD TO ASSESS NOVELTY POTENTIAL WITH FUNCTION SIMILARITY

This section proposes a method to assess novelty potential with function similarity. The first two subsections introduces the fundamental notions of this research, the novelty potential and the representation

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of function which is suitable for concept generation. The next subsection discusses the existing word similarity approaches based on data science from the viewpoints of processing function representation. It is followed by the proposed method of measuring function similarity.

3.1 Novelty potential

The novelty potential is introduced to see the potential of the two function concepts of which combination would lead to novel concepts. This research defines it as the length of time for a designer to think of multiple entity concepts (including both natural entities and artifacts) that will meet the two function concepts. The longer time, the more novelty potential.

Since it heavily depends on human ability, intuitive estimation is possible rather than measuring the time precisely. In the case study of this research, the following three-grade scale is defined.

- *Grade 1*: It is a common combination. Entity concepts which will meet the two function concepts can be come up with immediately.
- *Grade 2*: It is an uncommon combination. However, entity concepts which will meet the two function concepts can be come up with for a while.
- *Grade 3*: It is an uncommon combination. Not any entity concepts which will meet the two function concepts can be come up even if a designer spends plenty of time.

3.2 Representation of function

There are two major approaches of function representation, i.e., verb-object pair which has roots in the value engineering approach, and input-output flow which is usually used for system modeling. The former is more suitable for design concept generation, because it is so flexible that it can represent initial entities of early design stages. Based on the verb-object representation, this research employs a triplet of verb, object and modifier (Shimomura *et al*., 1998) which modifies a verb-objective pair. To allow the flexible representation, an object and/or a modifier can be omitted.

3.3 Approaches of measuring word similarity

While the current trend of artificial intelligence focuses on learning from big data of nonlinguistic information such as images, natural language processing has been one of the most attention-getting topics. The word similarity measurement is often used for ranking of document retrieval results. It is also used to quantify the similarity of design concepts written in linguistic representation such as function, e.g. (Cheong *et al*., 2017) , and to analyze the characteristics of idea generation process (Georgiev and Georgiev, 2018). There are two approaches to measure word similarity: lexical approach and distributional approach.

3.3.1 Word similarity in lexical approach

The lexical approach uses lexical database, that is, dictionary which defines hierarchical relationships of words or simple phrases, synonymous and antonym. WordNet is a popular lexical database. It was originally developed in English (Miller, 1995), and then deployed to the other languages.

The word similarity in lexical approach is usually defined with distance of hierarchy levels of words measured (Rada *et al*., 1989). For example, the following equation gives the similarity $s_l(w_1, w_2)$ of the measured two words w_1 and w_2.

$$s_l(w_1, w_2) = \frac{2d_c}{d_1 + d_2} \quad (1)$$

where d_1 and d_2 are the levels of w_1 and w_2, respectively. d_c is the level of the least common subsumer of the compared words in the hierarchy.

3.3.2 Word similarity in distributional approach

The distributional approach automatically extracts relationships of words or simple phrases with data science techniques from bodies of real world text, e.g., SNS, Wikipedia and so on. It is based on the distributional assumption that words used and occur in the same contexts tend to have similar meanings. The recently-popular method of this approach is word2vec (Mikolov *et al*., 2013). It uses two-layer neural networks trained to model linguistic contexts of words. It takes a large corpus and produces a

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several-hundred-dimension vector space, where a corresponding vector is assigned to each unique word in the corpus. Words that share common contexts in the corpus are located in close neighborhood to one another in the space. The vector space gives a cosine similarity between two vectors. It is often used as the word similarity in distributional approach $s_d(w_1, w_2)$, which is given by the following equation.

$$s_d(w_1, w_2) = s_{COS}(\vec{w}_1, \vec{w}_2) = \frac{\vec{w}_1 \cdot \vec{w}_2}{|\vec{w}_1||\vec{w}_2|} \quad (2)$$

where $\vec{w}_1$ and $\vec{w}_2$ are the corresponding vectors of w_1 and w_2, respectively. $s_{COS}(\vec{w}_1, \vec{w}_2)$ is the cosine similarity between $\vec{w}_1$ and $\vec{w}_2$.

3.3.3 Pros/cons

There are merits and demerits of the two approaches because of their differences of measuring algorithm. Table 1 shows the comparison with the four criteria set in terms of handling function concepts.'+' means that the corresponding approach is superior.

Table 1. Comparison of word similarity approaches

Criteria	Lexical approach	Distributional approach
1. Ontological information	+	-
2. Phrase similarity	-	+
3. Easy to use	-	+
4. Semantic correctness	+	-
Popular method	WordNet	word2vec

The first criterion is the ability of analyzing ontological information. The lexical approach can determine the ontological relationships of the words with the carefully-defined dictionary of hypernym, hyponym, synonymous and antonym. The distributional approach cannot do it because of the limitation of the distributional assumption. Take an example of noun words, *love*, *joy* and *disgust*. The lexical similarity can distinguish synonym and antonym, i.e., *love* and *joy* are of close meaning but *disgust* is more distant. Contrastingly, the distributional approach indicates that *love* is closer to *disgust* if they are often used in the same sentence in the analyzed corpus. It does not mean that either one is more accurate. Each approach measures a different aspect of word similarity. In general, the lexical approach is effective for high-level (generic) classification and the distributional approach is effective for low-level (specific) classification (Cheong *et al*., 2017).

The second criterion is the most important for handling function concepts. Function is usually represented by a set of words rather than a single word or a single phase. Measuring function similarity requires the consideration of such representation form. The distributional approach is superior as for this criterion. A linear combination of word vectors can be considered to be a vector of the phrase which the words constitute. The lexical approach does not have such operationability.

There is a trade-off between the third and fourth criterion. They are the two sides of the semantic issue. The lexical approach requires the elaboration of users to leverage the dictionary. Because a word has multiple meanings generally, a user should determine the database's direction word/phrase which matches the word measured. While many researches of semantic analysis are contending this issue, it cannot be automated so far. Contrastingly, the distributional approach can obtain plausible results without elaboration, while it may include semantically-buggy results.

3.4 Similarity of function concepts

The discussion of Section 3.3 indicates that it is necessary to complement the two approaches. Some specific combined techniques have been proposed. For example, Suryadi and Kim (2017) proposed a product feature clustering method based on user reviews in web pages, which uses word2vec for word similarity and then uses WordNet for word cluster similarity. Cheong *et al*. (2017) proposed a method to measure the similarity of functions in the input-output form by linear sum of the word2vec similarity and the WordNet similarity.

This research proposes the measuring method which is suitable for the function representation stated in Section 3.2. Since the second criterion of Table 1 is the most important for the function representation,

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the proposed method mainly employs the distributional approach, and complementarily uses the ontological information of the lexical approach. Since a verb plays a major role to represent the meanings of function, the lexical approach is used to measure the similarity between verbs. As stated in Section 3.3.3, there is a trade-off between the required elaboration and semantic correctness. This research analyzes the effects of the lexical similarity through case studies.

In the following explanation, f_1 and f_2 denote the function concepts measured. v_i, o_i, m_i denote a verb, objective and modifier of a function concept f_i, respectively.

1. A vector of f_i is given by the linear sum of vectors of the triplet elements $\vec{v_i}, \vec{o_i}, \vec{m_i}$. The following equation gives it.

$$\vec{f_i} = \frac{1}{N}(\vec{v_i} + \vec{o_1} + \vec{m_i}) \tag{3}$$

   – If either element of the triplet is empty, its vector is defined as $\vec{0}$. N is the number of no-zero vectors among $\vec{v_i}, \vec{o_i}, \vec{m_i}$. By definition of the function representation, $1 \leq N \leq 3$
   – If each element of the triplet consists of multiple words, its vector is defined as the linear sum of vectors of the words. For example, if a modifier m_i consists of M words $w_1, w_2, \cdots, w_M$, a vector of m_i is defined as follows.

$$\vec{m_i} = \frac{1}{M}\sum_{j=1}^{M} \vec{w_j} \tag{4}$$

2. The distributional similarity of f_1 and f_2 is given by the following equation of the cosine similarity.

$$s_d(f_1, f_2) = s_{COS}(\vec{f_1}, \vec{f_2}) \tag{5}$$

3. The lexical similarity of f_1 and f_2 is given by the similarity of verbs with the following equation.

$$s_l(f_1, f_2) = s_l(v_1, v_2) \tag{6}$$

4. The complemented similarity of f_1 and f_2 is given by the following equation.

$$s_c(f_1, f_2) = \frac{1}{2}(s_d + s_l) \tag{7}$$

Designers often use a negative form and a passive form for a verb phrase in a free representation. This research allows such representation in order not to interfere the designers' thinking process. As a function representation, they represent the same category of the concept, although they have different meanings grammatically. For example, all of *to move*, *not to move* and *to be move* represent the movement of something. This research treats them the same as a positive form in the above equations.

4 CASE STUDY

4.1 Design experiment

4.1.1 Method

This research performs a design experiment of retrospective analysis. In the case studies, the English WordNet and word2vec trained with the English Wikipedia are employed for the calculation of the proposed method explained in Section 3.4. The reason why the Wikipedia is chosen is that it contains an adequate amount of corpus for learning and it is relatively reliable more than other corpus such as SNS. The steps of the design experiment is as follows. The examinees are eight graduate students in the design engineering lab in Osaka university. The evaluators are three graduate students in the same lab who differ from the examinees.

1. A novel design, which already exists in the market, but is not common yet, is given to examinees.
2. The examinees analyze its design process as follows.
   (a) The examinees imagine initial entity concepts which have existed since before the given novel design appears. For example, fresh meat, spoiled meat and dry-bone meat are the initial entity concepts in the anecdote of Section 2.2.

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Table 2. Collected function concepts, measured similarities and rated novelty potential in design experiment (A): pot-in-pot refrigerator

f_1,f_2	$s_l(f_1,f_2)$	$s_d(f_1,f_2)$	$s_c(f_1,f_2)$	NP
to refrigerate food, to use natural phenomenon	0.333	0.250	0.292	7
to refrigerate food, not to use energy	0.333	0.345	0.339	5
to repeat action, to use heat vaporization	0.333	0.209	0.271	9
to change surroundings, not to use electric power	0.500	0.340	0.420	3
to use natural phenomenon, to refrigerate food	0.333	0.250	0.292	5
to keep low temperature, to use small space	0.400	0.400	0.400	5
to use heat vaporization or heat fusion, to confine cold air	0.333	0.401	0.367	6

One examinee is absent in this experiment.

(b) The examinees make alternatives of the classification of them by function concepts. The examinees are only asked to write every function by a triplet of verb-object-modifier of which object and/or modifier can be omitted. The terminology is not limited.
(c) The examinees choose the two functions which combination would lead to the given design.

3. Evaluators rate the novelty potential of the combination of the two function concepts made by the examinees.
4. Finally, the authors perform correlation analysis between the novelty potential rated by the evaluator and the similarity of the two functions measured by the proposed method.

4.1.2 Given novel designs

This research chooses two artifacts given to the design experiment: a pot-in-pot refrigerator and Adspecs glass. A pot-in-pot refrigerator is a cost-effective food storage with evaporative cooling process (Pandey and Pesala, 2016). It uses two nesting clay pots. The space between them is filled with sand and water which achieves evaporative cooling. Food is stored inside the inner pot. Adspecs is a cost-effective glass developed for people in developing countries (Douali and Silver, 2004). It has an adaptive liquid-filled variable focus lenses. Users can adjust their focal length to correct myopia without trained opticians nor replacing the lenses.

Both of them have been already utilized in developing countries. However, they are not common for neither the examinees nor the evaluators. So they are suitable for the design experiment of this research. An experiment is performed for each artifact, that is, (A) design experiment with pot-in-pot refrigerator, and (B) design experiment with Adspecs. It is expected that the verification will be more valid by performing multiple design experiments of different artifacts.

4.2 Results

Table 2 and Table 3 summarize the collected data from the design experiment (A) and the design experiment (B), respectively. They include the combinations of two function concepts f_1 and f_2 collected from the examinees, the similarity measured by $s_l(f_1,f_2)$ of Eq.(6), $s_d(f_1,f_2)$ of Eq.(5) and $s_c(f_1,f_2)$ of Eq.(7). *NP* is the sum of the three evaluators' rated numbers of the novelty potential, each of which is evaluated with the three-grade scale of Section 3.1.

According with the results, there are notable differences between the manners of function representation of the two experiments. No examinees use modifiers in the experiment (A), while all examinees use modifiers for either or both of the two functions in the experiment (B). They also use multiple words to represent objects in the experiment (B). Those characteristics make the function representation in the experiment (B) more complicated than that in the experiment (A). The differences are obtained accidentally, but they would help to discuss the measurement performance of the proposed method.

Figure 2 shows the results of correlation analysis of the collected data from the two experiments. In the six graphs, the vertical axis is the novelty potential, and the horizontal axis is (a) the lexical similarity $s_l(f_1,f_2)$ which is shown for comparison, (b) the distributional similarity $s_d(f_1,f_2)$ and the complemented similarity $s_c(f_1,f_2)$. R^2 denotes a coefficient of determination. A dotted line denotes a linear regression line.

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Table 3. Collected function concepts, measured similarities and rated novelty potential in design experiment (B): Adspecs

f_1, f_2	$s_l(f_1, f_2)$	$s_d(f_1, f_2)$	$s_c(f_1, f_2)$	NP
to complement bodily function with different shape, to adjust focal distance always	0.667	0.496	0.581	4
to adjust focal distance always, to be worn	0.333	0.146	0.240	5
to change lens thickness by transformation, to be worn	0.400	0.232	0.316	9
to change sight with liquid refractive index, to be worn	0.400	0.259	0.330	9
to adjust focal distance by changing thickness of lens, to fit people universally	0.571	0.226	0.399	7
to be worn, to customize focal distance without changing component	0.571	0.226	0.399	7
to be worn, to adjust focal distance without doctor	0.333	0.076	0.205	9
to reinforce bodily function, to adjust focal distance easily	0.571	0.421	0.496	3

The following facts can be found in the results.

1. All graphs show negative correlation between the measured function similarity and the rated novelty potential. That is, there is the positive correlation between the function distance and the novelty potential. It is consistent with the assumption of this research.
2. As for the experiment (A), the complemented similarity s_c gives the strong correlation with high coefficient ($R^2 \simeq 0.59$. It is 5% level of significance) which is the highest among the three methods.
3. As for the experiment (B), the complemented similarity s_c gives the correlation ($R^2 \simeq 0.27$). However, its coefficient is lower than that of the distributional similarity s_d ($R^2 \simeq 0.34$).
4. While the distributional similarity s_d in both experiments is not 10% level of significance, it gives the correlation of high coefficient (The p values are 17% and 13%, respectively).
5. The lexical similarity s_l gives the correlation of high coefficient in the experiment (A) ($R^2 \simeq 0.48$), but the just week correlation in the experiment (B) ($R^2 \simeq 0.17$).

5 DISCUSSION

5.1 Performance of assessing novelty potential to support concept generation

The results of the case studies shown in Section 4.2 indicate that the s_c and s_d have the significant ability to estimate the novelty potential based on the written function concepts. The notion of novelty potential would be a useful clue for generating novel concepts, although it relies on human intuition. The measurement of function similarity can be performed by the data science methods which are more scientific than the measurement of novelty potential.

Therefore, it is expected that the proposed assessment method can provide designers a useful clue to generate novel concepts . It will suggest appropriate classification concepts.

5.2 Reliability

The case studies compare s_c, s_d and s_l. The assessment performance of the complemented method s_c seems to be the best in a specific case. But it also seems to vary in different cases. It should be because of the differences of function representation manner pointed in Section 4.2. Since the function representation in the experiment (A) does not include modifiers, verbs take a more significant role to represent function concepts. The complementation of ontological information works well in the situation. Contrastingly, the function representation in the experiment (B) is more complicated because of modifiers and multi-word objects. In this situation, the ontological information of verbs does not work well.

More case studies are required to analyze the measurement reliability in detail. The finding about it obtained in this research is that there is a trade-off between the flexibility of function representation and the measurement reliability. If a designer wants the former, the incorporation of free form representation allowing modifiers and the distributional similarity method is effective. If a designer wants the latter,

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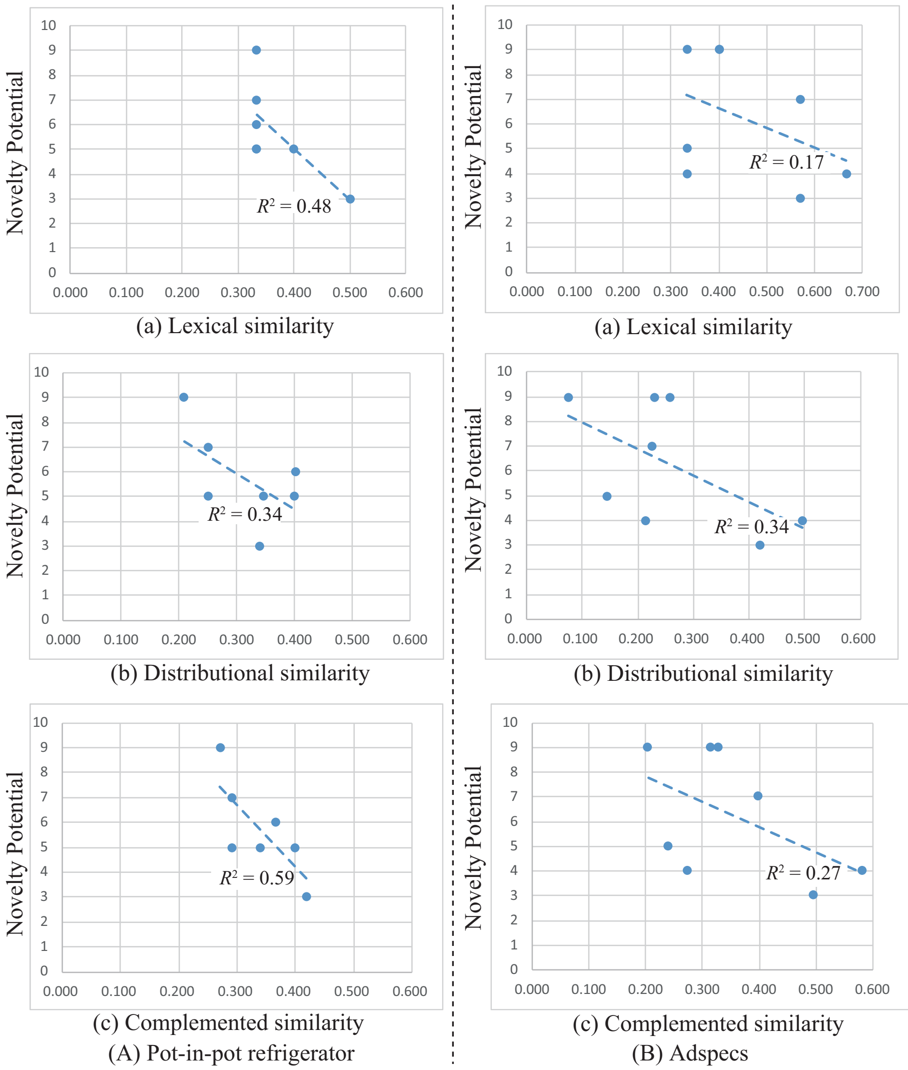

Figure 2. Correlation analysis of novelty potential and function similarities

the incorporation of more formal representation of function, such as a pair of verb-object with limited terminology, and the complemented similarity method is effective.

5.3 Notion of usefulness

This research does not focus on usefulness of generated concepts. Since a notion of usefulness is also important for creativity as well as a notion of novelty, a method to assess the usefulness of the combination of two functions is also required toward a method supporting innovative design concept generation. Based on the findings of this research, it is plausible to use the proposed measurement of function similarity for it. For example, the similarity between the function concept and the design problems to be solved may give the usefulness.

6 CONCLUSIONS

Building a scientific theory or methodology for innovative design concept generation is one of the most ambitious goals for design engineering researchers. Toward it, this research assumed that the more distant two function concepts chosen, the more novel idea would come up with by the combination of the two concepts. Based on the assumption, this paper proposed an assessing method of novelty potential of the combination of two function concepts by the function similarity based on the word similarity with WordNet and word2vec. This paper also discussed its possibility based on the case studies. The results support the possibility of the proposed method to support design concept generation. More case studies will be needed to refine the proposed method and embody a method to support design concept generation as stated in Section 5. As stated above, the prior works have developed some theories of

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creativity. The results in this research will be reviewed from their viewpoints. Those are included in our future works.

REFERENCES

Altshuller, G. (2005), *40 Principles: TRIZ Keys to Technical Innovation, Extended edition*, Technical Innovation Center Worchester, MA.

Chan, J., Fu, K., Schunn, C., Cagan, J., Wood, K. and Kotovsky, K. (2011), "On the Benefits and Pitfalls of Analogies for Innovative Design: Ideation Performance based on Analogical Distance, Commonness, and Modality of Examples", *Journal of Mechanical Design, Transactions of the ASME*, Vol. 133 No. 8, 081004. https://doi.org/10.1115/1.4004396

Cheong, H., Li, W., Cheung, A., Nogueira, A. and Iorio, F. (2017), "Automated Extraction of Function Knowledge from Text", *Journal of Mechanical Design, Transactions of the ASME*, Vol. 139 No. 11, p. 111407. https://doi.org/10.1115/1.4037817

Daly, S. R., Seifert, C. M., Yilmaz, S. and Gonzalez, R. (2016), "Comparing Ideation Techniques for Beginning Designers", *Journal of Mechanical Design, Transactions of the ASME*, Vol. 138 No. 10, p. 101108.

De Brentani, U. (2001), "Innovative versus Incremental New Business Services: Different Keys for Achieving Success", *Journal of Product Innovation Management*, Vol. 18 No. 3, pp. 169–187. https://doi.org/10.1016/S0737-6782(01)00071-6

Douali, M. G. and Silver, J. D. (2004), "Self-optimised Vision Correction with Adaptive Spectacle Lenses in Developing Countries", *Ophthalmic and Physiological Optics*, Vol. 24 No. 3, pp. 234–241. https://doi.org/10.1111/j.1475-1313.2004.00198.x

Fu, K., Fuge, M. and Brown, D. C. (2018), "Design Creativity", *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, Vol. 32 No. 4, pp. 363–364. https://doi.org/10.1017/S089006041800015X

Georgiev, G.V. and Georgiev, D.D. (2018) "Enhancing User Creativity: Semantic measures for Idea Generation", *Knowledge-Based Systems*, Vol. 151, pp. 1–15. https://doi.org/10.1016/j.knosys.2018.03.016

Han, J., Shi, F., Chen, L. and Childs, P. R. N. (2018), "A Computational Tool for Creative Idea Generation based on Analogical Reasoning and Ontology", *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, Vol. 32 No. 4. pp. 462–477. https://doi.org/10.1017/S0890060418000082

Hatchuel, A. and Weil, B. (2009), "C-K design theory: An advanced formulation", *Research in Engineering Design*, Vol. 19 No. 4, pp. 181–192. https://doi.org/10.1007/s00163-008-0043-4

Mikolov, T., Chen, K., Corrado, G. and Dean, J. (2013), "Efficient Estimation of Word Representations in Vector Space". https://arxiv.org/abs/1301.3781

Miller, G. A. (1995), "WordNet: A Lexical Database for English", *Communications of the ACM*, Vol. 38 No. 11, pp. 39–41. https://doi.org/10.1145/219717.219748

Pandey, R. and Pesala, B. (2016), "Heat and Mass Transfer Analysis of a Pot-in-pot Refrigerator Using Reynolds Flow Model", *Journal of Thermal Science and Engineering Applications*, Vol. 8 No. 3, 031006. https://doi.org/10.1115/1.4033010

Rada, R., Mili, H., Bicknell, E. and Blettner, M. (1989), "Development and Application of a Metric on Semantic Nets", *IEEE Transactions on Systems, Man and Cybernetics*, vol. 19 No. 1, pp. 17–30. https://doi.org/10.1109/21.24528

Ranjan, B. S. C., Siddharth, L. and Chakrabarti, A. (2018), "A Systematic Approach to Assessing Novelty, Requirement Satisfaction, and Creativity", *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, Vol. 32 No. 4, pp. 390–414. https://doi.org/10.1017/S0890060418000148

Shah, J. J., Vargas-Hernandez, N. and Smith, S. M. (2003), "Metrics for Measuring Ideation Effectiveness", *Design Studies*, Vol. 24 No. 2, pp. 111–134. https://doi.org/10.1016/S0142-694X(02)00034-0

Shimomura, Y., Yoshioka, M., Takeda, H., Umeda, Y. and Tomiyama, T. (1998), "Representation of Design Object based on the Functional Evolution Process Model", *Journal of Mechanical Design, Transactions of the ASME*, Vol. 120 No. 2, pp. 221–229. https://doi.org/10.1115/1.2826962

Suryadi, D. and Kim, H. (2017), "A Clustering and Word Similarity based Approach for Identifying Product Feature Words", *Proceedings of the International Conference on Engineering Design, ICED, 6 (DS87-6)*, pp. 71–80.

Taura, T. and Nagai, Y. (2013), "A Systematized Theory of Creative Concept Generation in Design: First-Order and High-Order Concept Generation", *Research in Engineering Design*, Vol. 24 No. 2, pp. 185–199. https://doi.org/10.1007/s00163-013-0152-6

Tomiyama, T., Breedveld, P. and Birkhofer, H. (2010), "Teaching Creative Design by Integrating General Design Theory and the Pahl & Beitz Methodology", *Proceeding of the ASME Design Engineering Technical Conference & Computers and Information in Engineering Conference*, Montreal, DETC2010-28444.

Yoshikawa, H. (1981), "General Design Theory and a CAD System", in Sata, T. and Warman, E. (Ed.), *Man-Machine Communication in CAD/CAM*, North-Holland, Amsterdam, pp. 35–38.