Research on intelligent heuristic design of industrial product

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Abstract. Effective and efficient design resource searching significantly inspires the product modeling design. This paper investigates the open innovation platform and design websites, constructs the retrieval algorithm model of design resources based on generative adversary network (GAN). The performance of retrieval algorithm model is tested by comparative experiments with that of Behance. Results show that the retrieval performance of the proposed model can reach the basically the same effects as Behance in conditional experiments, which shows that the GAN retrieval algorithm can be of high value and great potential for development in actual application. At the same time, results also show that taking the Red Dot award-winning works as the retrieval data can better stimulate the inspiration of designers and provide design reference for designers.

1. Introduction

Due to the lack of creativity and understanding of technology and market information, enterprises and designers will face the problems of low innovation efficiency and unsatisfactory innovation effect when they carry out product modeling design. Therefore, how to help enterprises and designers carry out innovative design with higher quality and efficiency becomes an urgent problem to be solved.

1.1. Research on open innovation

In 2003, Chesbrough\(^1\) put forward the concept of "open innovation" for the first time in his book "open innovation: new rules for technological innovation and making profits from it", which was highly valued by the business and academic circles. Today, open innovation is still a hot issue in the field of design management. Lopez Vega, Tell and Vanhaverbeke\(^2\) studied the innovation intermediary in open innovation projects, put forward four exploration paths for enterprises to acquire external knowledge, and analyzed the operation mechanism of these exploration paths with examples. Qureshi\(^3\) studied the participation of small and medium-sized enterprises in open innovation activities, selected small and medium-sized enterprises in Pakistan and the United Kingdom as research cases, and focused on how small and medium-sized enterprises solve the shortage of scarce resources by participating in open innovation activities. Kuwashima\(^4\) classified open innovation from the perspective of H W Chesbrough\(^5\), the proponent of open innovation and practitioners of open innovation activities, and studied the impact of open innovation mode.

1.2. Research on heuristic design

McKilligan et al.\(^6\) introduces a content analysis method, which can be used to discover the heuristic model in innovative product design, and extracted 40 principles of heuristic model by analyzing the key features and functional elements in more than 400 award-winning product designs. Trotta\(^7\) has
studied the bioinspired design method, which can be used to create innovative concepts in the creative generation stage, and its inspiration comes from the biological system, which can maximize the durability and efficiency of innovative concepts. Chen et al.[8] made clear that pictures play an important role in the concept development of innovative design, and studied the different effects of using pictures to stimulate designers’ creativity in different stages of sketch design. These documents show that digital resources such as pictures are of great help to the conceptual development of product modeling design. Pauw et al.[9] focuses on analogical transformation from biology to engineering, proposing guidelines to support such transformation and describes an interactive tool that can implement the guidelines. From the research of award-winning products and biosystems, many cases of inspiration patterns to support the design inspiration in product modeling design and engineering design are found.

This paper studies the related theories and application cases of open innovation and heuristic design, investigates the users of open innovation platform, design resource website and design heuristic tools. According to the mechanism of generative anti network, a database of heuristic design resources is constructed, the intelligent heuristic design model of industrial product modeling is constructed.

2. Methods

According to the previous articles, for various design resource websites, such as Behance, and the winning works of design events, such as Red dot and IF, the current retrieval method supports the screening according to the type, release time, likes, relevance and other indicators, but for different users(in the same screening and sorting rules), the content displayed in this retrieval method are the same. One of the problems in this situation is that the results of retrieval may not satisfy the designers, and the designers are unable to change the way of filtering and sorting. Above problems can be solved to a certain extent by using GAN algorithm.

2.1. Construction of heuristic design resource database

In this paper, more than 2100 pictures and corresponding product text descriptions under the classification of "product design" and "design concept" of the Red Dot Award in 2018 are selected as the data sources of the experimental retrieval data set. Pictures and text descriptions are interrelated in figure 1. Image retrieval is realized by retrieving text descriptions. The text description generally shows product modeling features, material, structure, usage and other information displayed in the pictures in detail. A paragraph of text description will correspond to one or more pictures, but these pictures describe the same product, so these pictures will be output as a group of pictures as search results. In the retrieval process, the algorithm calculates the correlation between keywords (i.e. "query") and each text description (i.e. "document"), arranges "documents" from high to low according to the correlation, and then finds the corresponding pictures according to these "documents".

Figure 1. Example of search data corresponding to pictures and text of award-winning works.

2.2. Heuristic resource retrieval algorithm based on GAN

2.2.1. Word frequency reverse document frequency and BM25 correlation. The relevance between query and document is measured by a score function. The score function contains two parameters: word frequency reverse document frequency (TF-IDF) and BM25 correlation.
In parameter TF-IDF, term frequency TF is calculated by dividing the number of times a word \( t \) appears in document \( D \) by the total number of words in document \( D \), as shown in equation (1), \( tf_{t,d} \) represents the word frequency of word \( t \) in document \( D \) and \( n_{t,d} \) indicates the number of times word \( t \) appears in document \( D \).

\[
tf_{t,d} = \frac{n_{t,d}}{\sum_k n_{k,d}}
\]

Reverse document frequency IDF is a measure of the universality of a word. Its calculation method is divided by the total number of files in the file set by the number of files containing the word \( t \), and then the quotient is obtained by taking the base 10 logarithm. In order to prevent the divisor (the number of files containing the word \( t \)) from being 0 in the calculation of IDF, the divisor is generally added to 1 for calculation. As shown in equation (2), \( idf_t \) means the frequency reverse document frequency of word \( t \), \(|D|\) indicates the total number of files in the file set, and \(|d: t \in d|\) indicates the number of files in the file set containing the word \( t \).

\[
idf_t = \log_{10} \left( \frac{|D|}{1 + |d: t \in d|} \right)
\]

Multiplying the word frequency TF and the reverse document frequency IDF is the TF-IDF value, as shown in equation (3), in which the \( tfidf_t \) means TF-IDF value of the word \( t \). The main idea of TF-IDF is: if a word or phrase appears frequently in a document, then TF is high, but rarely in other documents, it can be considered that this word or phrase belongs to this kind of document, which has a good ability of classification and is suitable for classification.

\[
 tfidf_t = tf_{t,d} \times idf_t
\]

The idea of BM25 correlation degree is similar to TF-IDF, and the parameter of "document length" is introduced on top of it. Generally speaking, the longer the document is, the more frequent the keyword will appear. Therefore, "document length" should be introduced to punish the score of long documents. See equation (4) for the calculation method of the correlation score of BM25, \( Score(t, d) \) means the correlation score of BM25 of words \( T \) and document \( D \); \( W \) is a coefficient, whose idea is similar to the frequency IDF of reverse documents, and its calculation method is shown in equation (5); \( k \) is the adjustment factor, \( k = 1 \) here, see equation (6) to calculate \( k \).

\[
 Score(t, d) = W \times \frac{n_{t,d} \times (k+1)}{n_{t,d}+K}
\]

\[
 W = \log_{10} \left( \frac{|D| - |d: t \in d| + 0.5}{|d: t \in d| + 0.5} \right)
\]

\[
 K = k \times \left( 1 - b + b \times \frac{dl}{avgdl} \right)
\]

In equation (6), \( b \) is the adjustment factor, here \( b = 0.75 \), \( dl \) is the length of the document, that is, the number of words contained in the document; \( avgdl \) indicates the average length of all documents. Enter a query, and the model will calculate the TF-IDF and BM25 correlation value of the query term with all documents; during initialization, the score function gives a coefficient for TF-IDF and BM25 correlation respectively, and then calculates the correlation score of the query with all documents.

2.2.2. Training of GAN model. According to corresponding literature, soft, interesting, fashion, warm, simple, portable, comfortable, organic, technical, stable, concise, emotional, elegant and ergonomic these 14 keywords related to product modeling are used in the first batch of retrieval. Pictures corresponding to the 10 documents with the highest score in each retrieval result are evaluated, then pictures related to the query keywords are selected, corresponding documents of these pictures are found. These documents with the query document serve as the true data \( X \) to train proposed GAN model. In the actual operation, the first batch of retrieval has been carried out 14 times, and 138 [query
document] pairs have been obtained, and these [query document] pairs have been manually marked by the author to see if they are relevant.

With these training data, this paper uses the GAN algorithm to get the generation model after training. According to the query entered by the user, the model can find the documents with the most relevance to the query, and arrange the documents containing query words from high to low. According to the existing related work of Ranknet[10], the model constructs a two-layer neural network as a score function in equation (7) to score the correlation degree; wherein, the [query document] pair \((t, d)\) is represented by vector \(x_{t,d}\), whose dimensions include TF-IDF and BM25 correlation degree, which represents the correlation degree score of query and document, and the coefficients \(W_2, W_1, B_1\) and \(W_0\) are model advantages. The hyperbolic tangent function \(\tanh()\) is used to make the influence of intermediate result change smoother.

\[
s(t, d) = w_2^T \tanh(W_1 x_{t,d} + b_1) + w_0
\]

In a training process of the model, generator selects the documents that it judges to be "relevant" according to the score function and marks them as 1; then selects some "irrelevant" documents from the remaining documents and marks them as 0. The generated [query document] will be sent to the discriminator \(d\) together with the true data \(x\), and the discriminator will compare the received generated data with the true data, and calculate the value of the loss function according to the difference between the two. The discriminator will also feed back the value of the loss function to the generator, so that both the discriminator and the generator can iteratively optimize the loss function until the value of the loss function is minimized and the training is completed. The score function will be used for retrieval.

In order to save time in the experiment, only the top ten retrieval results of the model are used for scoring each time, and they are arranged according to the correlation degree from high to low.

2.3. Retrieval model of design heuristics resource and experiment

In order to evaluate the performance of the retrieval model, this paper compares its retrieval effect with that of Behance. The comparative experiment is carried out as follows.

2.3.1. Experiment preparation. In the experiment, the GAN model is used as the experimental group, and Behance is the control group, and the same keywords are input. Both of them output a group of image sequences arranged according to the correlation degree. As shown in figure 2 the result page of image retrieval based on keywords of Behance. In order to ensure the comparability of retrieval results, "industrial design" is selected as the target field.

![Figure 2. Search results page of Behance.](image)

The score table of the experiment includes five indicators, namely, inspiration, usability, aesthetic value, unusual gains and similarity between the product shape in the pictures and the existing ideas.
2.3.2. Experimental process. Fifteen graduate students majoring in product design participated in the experiment. For the experiments, each participant needs to go through the following process:

- Participants are explained the purpose and process of the experiment;
- Participants select one group from these three groups tasks: bedside nightlight design for children, home speaker design for young working people and portable speaker design for retired elderly people;
- Participants simply describe their ideas about design tasks on white paper according to the selected task;
- Participants select two keywords from 14 words;
- Each key word is input into GAN retrieval model and Behance respectively, and the top 10 retrieval results obtained by two ways are selected respectively, the pictures of these 20 retrieval results are interspersed to the participants;
- Participants rate 20 pictures retrieved by a keyword respectively. They rate the 5 indicators: inspiration, usability and aesthetic value, unusual gains and similarity with a score of 1-7. Each participant is asked to rate 40 pictures in two groups.

3. Results

3.1. Data analysis

According to the users' scores for the retrieval results of the two models obtained in the experiment, in order to compare the differences between different intervals of the retrieval results, this paper calculates the mean and variance of the user's scores for the first three, the first five and all ten pictures, and the results are shown in table1 and table 2. Then, this paper calculated the p-value of the significant difference between the two groups, and the results are shown in table 3. The p-values of the two groups are greater than 0.05, indicating that there is no significant difference between the two groups.

| Table 1. Means of Behance group and GAN group. |
|-----------------------------------------------|
| Inspiration | Usability | Eesthetic value | Unusual gains | Similarity |
| Behance 1-3  | 3.90      | 3.28           | 3.93          | 3.51       | 2.58       |
| GAN 1-3      | 3.78      | 3.46           | 4.06          | 3.51       | 2.34       |
| Behance 1-5  | 3.81      | 3.26           | 3.83          | 3.53       | 2.62       |
| GAN 1-5      | 3.85      | 3.49           | 4.15          | 3.42       | 2.47       |
| Behance 1-10 | 3.88      | 3.39           | 3.99          | 3.55       | 2.52       |
| GAN 1-10     | 3.81      | 3.42           | 4.12          | 3.39       | 2.36       |

| Table 2. Variances of Behance group and GAN group. |
|-----------------------------------------------|
| Inspiration | Usability | Eesthetic value | Unusual gains | Similarity |
| Behance 1-3  | 3.64      | 2.76           | 3.50          | 3.71       | 2.83       |
| GAN 1-3      | 3.52      | 3.46           | 3.63          | 3.62       | 2.54       |
| Behance 1-5  | 3.64      | 2.96           | 3.31          | 3.63       | 3.03       |
| GAN 1-5      | 3.67      | 3.34           | 3.46          | 3.39       | 2.55       |
| Behance 1-10 | 3.60      | 3.28           | 3.42          | 3.58       | 2.71       |
| GAN 1-10     | 3.51      | 3.17           | 3.32          | 3.41       | 2.27       |

| Table 3. p value of significance difference of scores. |
|-----------------------------------------------|
| Inspiration | Usability | Eesthetic value | Unusual gains | Similarity |
| Behance 1-3  |           |                |               |            |
| GAN 1-3      |           |                |               |            |
| Behance 1-5  |           |                |               |            |
| GAN 1-5      |           |                |               |            |
| Behance 1-10 |           |                |               |            |
| GAN 1-10     |           |                |               |            |
| Retrieval results of Behance and GAN 1-3 | 0.67 | 0.50 | 0.66 | 1.00 | 0.34 |
| Retrieval results of Behance and GAN 1-5 | 0.88 | 0.26 | 0.13 | 0.60 | 0.45 |
| Retrieval results of Behance and GAN 1-10 | 0.63 | 0.86 | 0.39 | 0.28 | 0.21 |

3.2. Empirical conclusion

Through the statistical analysis of the scores of the two groups, there is no significant difference between the two groups, and then the conclusion is drawn that the GAN retrieval model obtained in this paper is basically consistent with the retrieval effect of Behance.

At the same time, the product content of Behance includes title, description and label. However, in practice, the author has noticed that the search results of Behance are highly related to the label. Some products do not have keywords in the title and description, but the keywords appear in the label. At this time, the ranking of the search results is also relatively high. These labels are dynamically updated and are generated by the website user. Added tags are consistent with user's subjective feelings, and these tags need a long time of data accumulation. In contrast, the content of Red Dot award-winning works retrieved by GAN retrieval model is static, only including classification, title, description and comments, and will not change after the award results are published. In addition, Behance has a large amount of content information, while the experimental retrieval data set only contains more than 2100 pieces of data, which has a huge difference in data volume.

However, in this case, the GAN retrieval model can still achieve the same retrieval effect as that of Behance, which shows that the GAN algorithm plays an important role, the GAN retrieval model has significant effect, and has good application value and development space. At the same time, this results also show that taking the Red Dot award-winning works as the retrieval data can better stimulate the inspiration of designers and provide design reference for designers.

4. Conclusion

The two key stages in industrial product modeling design are design research and scheme generation. However, in these two stages, due to the limited knowledge, skills and cognition of designers themselves, it is difficult to obtain innovative ideas. Therefore, this paper focuses on the intelligent heuristic design of industrial product modeling. It proposes that GAN can be used to fit the user's preference for retrieval, so as to improve the efficiency of retrieval, and then to help the development of creative schemes. The mechanism of GAN in heuristic design resource retrieval is studied. Based on this, a retrieval model based on GAN is constructed, and then a comparative experiment is carried out to compare its retrieval effect with that of Behance. The experiment results show that the proposed model can achieve the same retrieval effect as Behance, and improve the retrieval efficiency, which further can enhance the creative project.

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