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Exploration of a Concept Screening Method in a Crowdsourcing Environment

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Abstract. As an effective way to aggregate a crowd's wisdom, crowdsourcing has attracted much research attention in recent years. Especially for product design and development, crowdsourcing shows huge potential for creativity and has been regarded as one important approach to acquire innovative concepts. However, there is still a challenge to make use of crowdsourcing in product design: how to review the large number of crowdsourcing concepts efficiently. To tackle this problem, a concept screening method is proposed in this article so as to i) improve the efficiency of evaluating crowdsourcing results; and ii) assist designers in identifying promising design candidates for further evaluation. Firstly, web mining technique is applied to extract textual information from Webs and tokenize text contents into word tags. Secondly, a concept similarity estimation process is designed to calculate the similarity between design requirements and crowdsourced concepts. During the estimation process, three situations are considered: 1) similarity caused by repeated tokens; 2) similarity caused by synonymous tokens; and 3) similarity in terms of design knowledge hierarchy. Finally, concepts are clustered based on their similarities, and the ones, which meet design requirements better, will be identified as promising candidates to be further reviewed by designers. To validate the proposed method, a pilot study on future PC design is presented.

Keywords. Crowdsourcing, web mining, design knowledge hierarchy, concept clustering

Introduction

Nowadays, crowdsourcing is applied widely in various industries [1]. In product design and development, crowdsourcing has been recognized as an effective way to access external resources and to aggregate a crowd's wisdom in order to bring about more chances to achieve better design concepts [2]. Taking Proctor & Gamble as an example, the most challenging problems are solved by 'InnoCentive', and the problem solving rate has increased to 30%. In another example, Dell has set up an idea storm platform to collect comments and suggestions for all Dell products from Internet users. In addition, Wikipedia, Amazon's Mechanical Turk and iStockPhoto.com are all good examples that take advantage of the tremendous numbers of Web users. Therefore, crowdsourcing appears to be a promising way to solicit external resources to improve product competitiveness [3, 4].

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Actually, a number of research studies have been devoted to crowdsourcing, the scope of which has covered the authentication of crowdsourcing's power in acquiring useful data [5] and in the identification of factors which may influence the crowdsourcing effect [6].

Although crowdsourcing shows potential in reaching better design concepts, it is still challenging to process large amounts of crowdsourcing results efficiently. Traditionally, firms rely on their internal R&D to screen and evaluate design concepts; however, a problem comes out that the workload to review crowdsourcing responses manually is very heavy. Moreover, the reliability of evaluation results heavily relies on designers' personal knowledge and experience. To improve the efficiency and reliability of concept evaluation in a crowdsourcing environment, we explore a concept screening method to assist designers in identifying useful responses from crowdsourcing results.

1. Related work

Crowdsourcing was firstly coined by Howe in the article "The Rise of Crowdsourcing" in 2006 [7]. Crowdsourcing is defined as '*the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call*' [7]. It is an important method to draw upon large numbers of people to contribute their knowledge [13, 14]. With the rapid development of the Internet, Web 2.0 provides an open platform to connect enterprises with worldwide consumers. Firms have more channels to communicate with users and can acquire useful knowledge from Internet users. Regarding concept generation, the applications of crowdsourcing can be in multiple forms; for example, new idea and innovation creation, design contests, problem solving, new product development and marketing, advertising, and brand building purposes [2].

Generally, crowdsourcing can be schematically depicted as in Figure 1. The employer/assigner (right side) submits a task (human intelligence task – HIT) to a mediator, viz. the crowdsourcing platform, and defines the requirements, reward rules, and task duration. Online workers/providers (left side) who are interested in this task can work on it and submit their solutions to the mediator after completion. These solutions will be forwarded to the employer who will pay the participants if their solutions are approved [15].

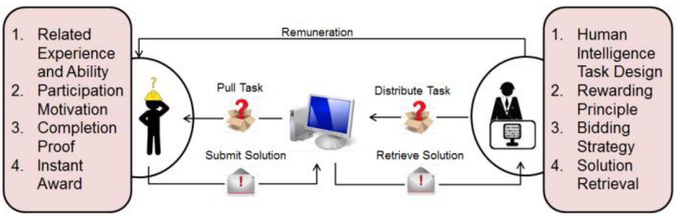

Figure 1. Typical crowdsourcing scheme

As the major motivation of participants to contribute their ideas is monetary reward, it is unavoidable that some participation is perfunctory [8]. Moreover, there is a lack of effective supervision mechanism in practical crowdsourcing system, and it further increases the chances of receiving unqualified submissions. Therefore, the quality of crowdsourcing results is actually hard to control. On the other hand, the amount of crowdsourcing results is oftentimes huge, thus the workload of designers to review crowdsourced concepts is very heavy.

Based on the analysis of current crowdsourcing studies for concept generation, it is indicated that

- There is a need of an effective and efficient method of screening product concepts in a crowdsourcing environment.

2. Methodology

The proposed method focuses on the processing of text information of crowdsourcing concepts. Through estimating the information content similarity between crowdsourcing concepts and design requirements, the concepts, which fit the design requirements/criteria better, are identified as promising design candidates to be further reviewed by designers. Generally, this method is divided into three main stages.

2.1 Web mining of online crowdsourcing responses

In a crowdsourcing environment, concepts are generated and collected through online human intelligence tasks (HITs) which are established based on Web 2.0. In practical case, design requirements are posted online, and Internet users, who are interested in this project, can contribute their ideas. Normally, crowdsourced concepts are presented in textual descriptions and graphic presentations. However, image data processing is beyond our scope, and we focus on the text information processing of crowdsourcing concepts. To discover text patterns, web mining technique is applied to assist the extraction of texts from Webs, and afterwards meaningful words (e.g. nouns, verbs, adjectives, excluding preposition and postposition) are recognized and tagged as tokens.

2.2 Concept analysis based on semantics and design knowledge

Having the tokens after web mining, information contents should be analyzed. In particular, '*synonym set*' is proposed in this work to fragmentize the tokens of one concept into several sets according to their semantic distance. Tokens (nouns) belonging to the same category (e.g. water, sea, lake) or representing the same thing (e.g. hand phone, cellphone, mobile phone) can be clustered together, and tokens (adjectives) describing the same aspect (e.g. feasible, workable, practicable) can be grouped into one set. Generally, tokens in the same synonym set have certain similar lexical meaning, thus one synonym set is treated as a whole during processing. To explain, Concept 1 has a synonym set A={water, sea, lake}, and Concept 2 has a synonym set B={water, sea wave, stream}. To compare the similarity between Concept 1 and 2, it is considered to comprehensively compare set A and set B, since all of the member words have relations with each other. However, the specific relations between these tokens are not the same, and a hierarchical structure is needed to outline the specific relations between them. For example, given a synonym set {lake, stream, water, sea, waterfall, sea wave …} which contains the nouns belonging to water system, a lexical hierarchy can be further derived as shown in Figure 2.

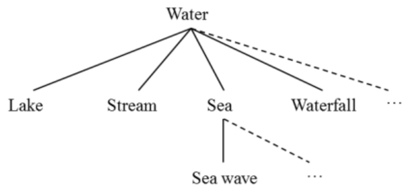

Figure 2. Lexical hierarchy of a synonym set

From this hierarchy, the tokens at higher level are broader terms with relatively less informativeness [12]. In the same sense, the tokens at lower level are more specific and contain clearer information. If an external word is synonymous with one member of a synonym set, it indicates that this word also has relations with other set members, since they may describe the same thing or describe the same topic from different respects. It is also the reason why the synonym set should be considered as a whole during the estimation of concept similarity. Surely, the relations between synonym set members and the external word are not the same and quantitative estimation methods should be developed accordingly.

Regarding the identification of synonyms, lexical database is needed to provide the dictionary resources to support the recognition of synonyms. Actually, an English lexical database *WordNet* has been developed by Princeton University [9]. This database organizes English words based on their lexical meaning and lexical category. Users can type in a word, and *WordNet* gives the meaning, synonyms, antonyms, familiarity, etc. In this article, *WordNet* is used to assist the identification of synonyms.

2.3 Concept similarity analysis

As mentioned above, it is hard to ensure the quality of every response in a crowdsourcing environment. To filter out the unqualified concepts, a comparison between crowdsourced concepts and design requirements is necessary. Concept similarity analysis aims to extract the ideas meeting design requirements from large amounts of crowdsourcing results in order to reduce designers' workload.

Considering the estimation of concept similarity, it is necessary to recall the notion of domain ontology to assist in the similarity reasoning of domain interests [10].

Definition 2.1 (*Domain ontology*). Domain ontology is specified by a set of concepts and a set of semantic relations, such as *generalization, part of, relatedness, similarity*, etc. In particular, the *similarity* relation is a ternary relation:

$$similarity(c_i, c_j, as(c_i, c_j))$$

where c_i, c_j are concept names, and $as(c_i, c_j)$ is the similarity degree in the interval [0.0, 1.0].

For similarity analysis, three main situations are considered: similarity caused by repeated words; similarity caused by synonymous words; and similarity relation due to design knowledge. Accordingly, three types of quantitative estimation methods are developed to calculate concept similarities in different situations.

2.3.1 Estimation of concept similarity in terms of repeated tokens

For similarity caused by repeated tokens, a value assignment method is presented in (1). If token 1 of Concept 1 is the same with token 2 of Concept 2, 1 will be assigned to the similarity degree. If tokens from two concepts are different, 0 will be assigned.

$$as(T_1,T_2)=\begin{cases}1, & if \quad T_1=T_2\\ 0, & if \quad others\end{cases} \tag{1}$$

The similarity between two synonym sets S_a and S_b can be obtained through combining the value assigned to the repeated tokens.

$$M(S_a,S_b)=\max(\sum_{T_1\in S_a,T_2\in S_b} as(T_1,T_2)) \tag{2}$$

For example, given $S_a=\{\text{sea, lake, stream}\}$ and $S_b=\{\text{sea, river, water}\}$, similarities between tokens of two sets are: $as(sea,sea)=1$; $as(lake,river)=0$; $as(stream,water)=0$ … Then similarity between S_a and S_b can be computed:

$$M(S_a,S_b)=\max(\sum as(S_a,S_b))=1+0=1.$$

2.3.2 Estimation of concept similarity in terms of synonymous tokens

To estimate the similarity between synonyms, the *Information content similarity* method proposed by Formica is applied [11].

$$as(n_1,n_2)=\frac{2\log_2 p(n')}{\log_2 p(n_1)+\log_2 p(n_2)} \tag{3}$$

$$-\log_2 p(n')=\max_{n\in Sh(n_1,n_2)}[-\log_2 p(n)] \tag{4}$$

$$p(n)=\frac{TF(n)}{N} \tag{5}$$

Where n_1 and n_2 are concept nouns from S_a and S_b respectively; n' is a concept noun providing the maximum information content shared by n_1, n_2, namely $Sh(n_1,n_2)$; *N* is the total number of observed instances of tokens in the corpus; *TF* is term frequency.

Take the example in Figure 2 to explain. *Water* is upper-level token; *lake* and *stream* are lower-level tokens and share the content of *water*. Given $p(water)=0.005$; $p(lake)=0.002$; $p(stream)=0.001$; then

$$as(n_1,n_2)=\frac{2\log_2 p(n')}{\log_2 p(n_1)+\log_2 p(n_2)}=\frac{2*\log_2 0.005}{\log_2 0.002+\log_2 0.001}=0.808$$

Thus, the similarity between two synonymous sets S_a and S_b can be obtained through combining the similarity of synonyms from the two sets.

$$E(S_a,S_b)=\max(\sum_{n_1\in S_a,n_2\in S_b} as(n_1,n_2)) \tag{6}$$

2.3.3 Estimation of concept similarity in terms of design knowledge hierarchy

In concept evaluation, an important challenge is to reveal the relations between different notions from the perspective of design knowledge. For instance, term '*ease of use*' is different from '*user friendly*' in semantics. However, *ease of use* is one common measure to embody *user friendly* in product design process. To ensure the screening reliability, similarity in terms of design knowledge should also be considered. To recognize the relations based on design development knowledge, *design knowledge hierarchy* is developed.

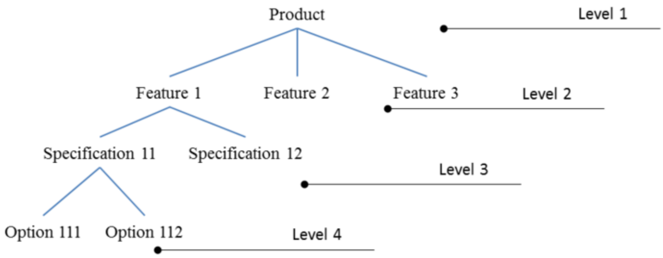

Figure 3. Design knowledge hierarchy

As shown in Figure 3, this hierarchy provides a reasoning approach to bridge tokens describing product design at different design knowledge levels. For example, *projector* is a kind of *function*, and it indicates they have relations from design perspective. To deeply concern, design knowledge hierarchy is actually a structure outlining the *a-part-of* and *a-kind-of* relations between design respects. To estimate this type of similarity, a parameter of '*extension rate* α ' is proposed to represent the similarity between adjacent levels. To explain, if the extension rate between level 2 and level 1 is $\alpha_{l_{1,2}}$, the tokens belonging to level 2 have a possibility of $\alpha_{l_{1,2}}$ to be similar with tokens at level 1 from design perspective. Considering that the exact meaning of a token should be identified in certain context, vagueness may exist in using design knowledge hierarchy to estimate concept similarity. For example, *small* can be used to describe *size*, and also used as *the slender part of the back*. To embody the vagueness, α should be a number between [0,1).

Therefore, the similarity between two tokens at different design knowledge hierarchy levels can be computed using (7). Accordingly, the similarity in terms of design knowledge between two synonym sets can be obtained through formula (8).

$$as(T_{l_m}, T_{l_n}) = \prod_{i=m}^{n-1} \alpha_{l_{i,i+1}}; m < n \tag{7}$$

$$W(S_a, S_b) = \sum_{T_{l_m} \in S_a, T_{l_n} \in S_b} as(T_{l_m}, T_{l_n}) \tag{8}$$

Finally, the overall concept similarity takes into account the similarities under the three situations discussed above. Furthermore, as concepts are often described in multiple dimensions, weightings and priorities of different dimensions should be considered. For example, some dimensions may be focused more by designers, and it leads to the need of a parameter to emphasize the priority. Therefore, weightings and priorities can be added to improve the computation flexibility. Given two concepts which both consist of two dimensions,

$$C_1 = (S_{a1}, S_{a2})$$
$$C_2 = (S_{b1}, S_{b2})$$

$$Sim(C_1, C_2) = \left(\frac{M(S_{a1}, S_{b1}) + E(S_{a1}, S_{b1}) + W(S_{a1}, S_{b1})}{N_1} w_1 p_1, \ \frac{M(S_{a2}, S_{b2}) + E(S_{a2}, S_{b2}) + W(S_{a2}, S_{b2})}{N_2} w_2 p_2\right) \tag{9}$$

where S_{a1} and S_{a2} are two synonym sets of Concept 1; S_{b1} and S_{b2} are two synonym sets of Concept 2; S_{a1} and S_{b1} have synonym relation in dimension 1; S_{a2} and S_{b2} have synonym relation in dimension 2; N_1 is the total number of tokens describing dimension 1; N_2 is the total number of tokens describing dimension 2; w_1 is the weighting of dimension 1; w_2 is the weighting of dimension 2; p_1 is the priority assigned to dimension 1; p_2 is the priority assigned to dimension 2.

2.4 Concept clustering and decision making

In this stage, clustering technique is adopted to classify crowdsourcing concepts according to their content similarity with design criteria. The concepts, which embody the design criteria better, are grouped together and identified as promising candidates to be further reviewed by designers. During decision making, experts' opinions and designers' experiences are important to deeply analyze the common characters of concepts belonging to the cluster which has the best overall similarity, so as to acquire inspirations for the creation of more innovative concepts.

3. Evaluation of the proposed method

To validate the proposed method, a pilot study is performed. A crowdsourcing design project of *Future PC design* on *Designboom* is used. To evaluate the concept screening effect of the proposed method, it is also carried out to invite designers or professionals to review the crowdsourcing results. Through a comparison between the results calculated by the proposed method and evaluated by designers, the concept screening effect of the proposed method can be estimated. Considering the workload of designers to review and compare these concepts, the number of crowdsourcing concepts to be analyzed is controlled at 20. Therefore, 20 crowdsourcing results are randomly selected from more than 150 crowdsourcing responses.

- **Stage 1: web mining**

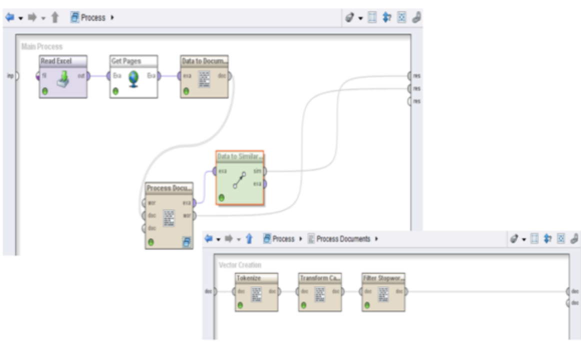

Figure 4. Rapidminer Main Processes and Vector Processes

As shown in Figure 4, a data mining tool *Rapidminer* is applied to conduct the text extraction and tokenization procedures. All the website links are recorded in an excel file, through reading this excel, *Get Pages* operator will crawl the web contents and discover text patterns. Afterwards, these textual data are organized into a document and will be processed by a *Process Document* operator which consists of three vector operators: *Tokenize*, *Transform Cases*, and *Filter Stopwords*. In addition, *Stem* operator is also added to filter the stem words, so that the transformational words can be processed as one stem.

- **Stage 2: Concept analysis**

Based on the web mining results, tokens of concepts are analyzed. Firstly, design requirements are studied. Actually, it is stated clearly that there are five design criteria: 1) innovative, 2) reliable, 3) user-centric/user-friendly, 4) appeal, and 5) feasible. To be compared with design requirements, synonym sets of 20 concepts are generated at these five respects. Therefore, each concept is represented as $C=(S_1,S_2,S_3,S_4,S_5)$, S_1 is synonym set about 'innovative', and similar with other synonym sets. For example, tokenization result of concept 1 is shown below.

uniqu lifebook design young peopl want notebook outlook . user creat person , stylish impress case cover us photo default softwar , cover shift conveni 3 side button . cover design cover , photo frame , enabl user captur moment life us lifebook . order go green , design colour e ink technolog help reduc power consumpt batteri life . cover displai date time , updat new headlin smart programm thu user check inform easili switch notebook

Synonym sets are generated about five design criteria and presented as follows.

$$C_1=(\{Uniqe, new, create\}, \{help, check\}, \{easily, convenient\}, \{\}, \{button, techno\log y, power, battery\})$$

Among these synonym sets, the first and forth sets are generated according to semantic similarity, and other three sets are obtained through design knowledge hierarchy.

- **Stage 3: Concept similarity**

As mentioned above, the similarity situations of these 5 respects are not the same. Similarity caused by repeated tokens should be detected for every concept. In addition, the first and forth synonym sets (i.e. S(innovative), S(appeal)) are built based on semantics, and other sets (i.e. S(reliable), S(user-centric/user-friendly), S(feasible)) are generated from design knowledge hierarchy perspective. Therefore, corresponding estimation methods are applied to calculate the similarities in 5 dimensions.

Furthermore, the contents stating design requirements are treated as the ideal one to be compared with 20 crowdsourced concepts. However, the similarity degree of this ideal one is not 1. Since design requirements are not just five words after all, the total token number should also be considered in calculation of the similarity degree as in (9).

Table 1. Calculation results of concept similarity degree

Concepts	Total token number	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5
Ideal	28	0.0357	0.0357	0.0357	0.0357	0.0357
Concept 1	65	0.0221	0.0292	0.0754	0	0.057
Concept 2	68	0	0.0419	0.05882	0	0.1593
Concept 3	66	0.0117	0.0144	0.1015	0	0.1094
Concept 4	47	0	0.0404	0.0787	0	0.0970
Concept 5	96	0	0.0198	0.0208	0	0.0198
Concept 6	124	0.0102	0	0.0468	0.0081	0.1544
Concept 7	151	0.0128	0.0063	0.0440	0	0.0359
Concept 8	44	0	0	0.0898	0	0.0831
Concept 9	61	0.0254	0.0467	0.0770	0	0.0452
Concept 10	118	0.0066	0.0081	0.0572	0	0.0620
Concept 11	77	0	0.0123	0.05	0	0.1061
Concept 12	115	0.0067	0	0.0735	0	0.1330
Concept 13	120	0	0	0.0317	0	0.0230
Concept 14	50	0	0	0.056	0	0.0361

Concept 15	80	0	0.0119	0.0481	0	0.1128
Concept 16	90	0	0	0.0539	0	0.1219
Concept 17	51	0	0.0373	0.0186	0	0.1593
Concept 18	68	0	0.0140	0	0	0.1194
Concept 19	68	0	0	0.0566	0	0.0803
Concept 20	43	0	0	0.0663	0	0.1270

- **Stage 4: Concept clustering and decision making**

Based on the similarity in 5 dimensions, all of 21 concepts are clustered by *k*means clustering. To simplify the calculation process, these concepts are classified into 2 groups to simply distinguish the cluster more similar with the ideal one. Surely, to further explore or improve the clustering reliability, *k* can be set as other values. Clustering result is presented in the figure below.

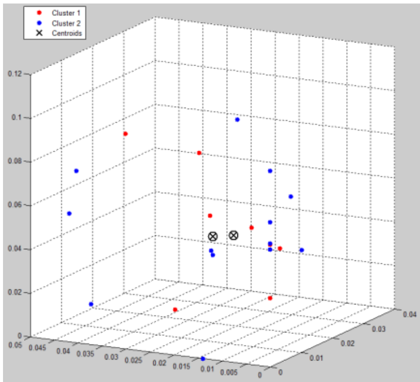

Figure 5. Concept clustering result

Clustering 1 = $\{C_{Ideal}, C_1, C_5, C_7, C_9, C_{10}, C_{13}, C_{14}\}$

Clustering 2 = $\{C_2, C_3, C_4, C_6, C_8, C_{11}, C_{12}, C_{15}, C_{16}, C_{17}, C_{18}, C_{19}, C_{20}\}$.

From the clustering result, a primary indication is that the concepts in the same cluster with the ideal one can be regarded as promising candidates matching design requirements better. To validate this result, a group of Ph.D. students with design background and related experiences is invited to review and rank all of the 20 concepts according to the project requirements, and the ranking is shown in Table 2.

Table 2. Concept ranking by designers

Ranking	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Concept	7	9	13	1	14	8	6	18	19	16
Ranking	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Concept	17	3	2	20	15	11	12	10	4	5

Through comparing the clustering results and concept ranking evaluated by designers, it can be found that the rough screening accuracy of the proposed method referring to designers' review results is 71.43% (5/7) which is acceptable.

4. Discussion and Conclusion

In this paper, a concept screening method based on concept similarity analysis is proposed so as to assist the processing of large crowdsourcing concepts. In particular, web mining technique is applied for text extraction and tokenization. Afterwards, concept similarities between design requirements and crowdsourced concepts are calculated. During the similarity estimation process, three types of similarity situations are considered: 1) similarity caused by repeated tokens; 2) similarity caused by synonymous tokens; and 3) similarity in terms of design knowledge hierarchy. Domain ontology is referred to assist the recognition of synonyms, and design knowledge is used to reveal the similarity relations from the design perspective. Finally, concepts are clustered based on similarities, and the concepts, which meet design requirements better, are identified. Through a pilot study on future PC design, it appears that the proposed method is helpful in selecting promising useful ideas.

However, there are still some limitations of this work. For example, the number of crowdsourced concepts analyzed in this case study is 20, which is not enough compared with the total 150 crowdsourcing results. In future research, it will be considered to validate this method on a larger scale to further demonstrate the efficiency of the proposed method in processing large numbers of crowdsourcing results.

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