Providing an Appropriate Search Space to Solve the Fatigue Problem in Interactive Evolutionary Computation.

Article *in* New Generation Computing · June 2005

DOI: 10.1007/BF03037489 · Source: DBLP

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Revised 9 September 2004

Abstract The user fatigue problem in interactive evolutionary computation (IEC) is a complex and interesting issue. If the IEC search space is created from the experience or knowledge of domain experts rather than from users' values, it causes two potential problems which lead to fatigue problems in IEC: 1) inefficiency, because the user's favorite solutions do not exist in the search space and 2) boredom, because users must look through the search space for an extended period of time, which is an uninteresting process. Therefore, we propose a customer values-based IEC model, solving the fatigue problem by avoiding the potential problems. The search space of a combination problem is constructed using a set of attributes and its attribute levels. In our model, we first collect the users' values, then transform the values into a set of objectives, and finally provide mapping between the objectives and attributes (or attribute levels). A case study involving the design of mineral water bottles was used to verify the anti-fatigue capability of the users when using the proposed model. For comparison with the traditional domain knowledge-based model, we built two IEC systems, a customer values-based system and a domain knowledge-based system, and conducted a user burden test and a system efficiency test over a two-week period. The results of both tests show that our proposed system performed better than the traditional domain knowledge-based system in designing mineral water bottles. This evidence implies that transforming customer values into a search space is a useful strategy to reduce user burden.

Keywords: Interactive Evolutionary Computation, User Fatigue, Value-focused Thinking, Product Design, Customer Value

§1 Introduction

Dawkins established the primary concept of interactive evolutionary computation (IEC) in 1986, [3] and Caldwell and Johnston [2] and Smith [20] introduced it to the evolutionary computation research community in 1991. IEC has been applied in nearly 20 application domains in the research community [21] and has also been used in real world cases. For example, Affinnova (http://www.affinnova.com/), founded in 2000, has used its IDEA™, or Interactive Design by Evolutionary Algorithm, technology to identify and evolve the most preferred product(s) for a given representative group of consumers or a desired target market.

How to effectively support customers designing a preferred product is an interesting topic in marketing research. MIT's Virtual Customer Initiative (http://mitsloan.mit.edu/vc/), a multidisciplinary research project, is developing and testing new theories and methods to improve the speed, accuracy, and usability of customer input in the product development process. We find that IEC is naturally suited to be the core technique of product design systems.

IEC users are asked to interact with the system during the evolution process, and are forced to take on heavy loads during interactions throughout the evolution generations. These heavy loads result in the primary fatigue problem in IEC. Some researchers have attempted to reduce the fatigue burdens, but currently it is still simply an interesting topic for research.

The search (or solution or product) space of IEC or conventional marketing research methods was designed based on domain experts' knowledge, but we believe this search space does not meet the customers' values (or objectives). If users must search for their products in such a space, two potential problems (inefficiency, because their favorite product does not exist in the product space, and boredom, because users must search through uninteresting product space) will cause the fatigue problem.

Therefore, we propose an effective method to create a search space that meets the customer values (or objectives), and integrates the space into a customer values-based IEC model to reduce user burden when designing their preferred products.

In Section 2, we briefly review papers related to IEC user burden reduction. In Section 3, we describe the proposed customer values-based IEC model, and to verify the performance of the model, a case study with two experiments is introduced in Section 4. The experimental results are shown in Section 5, and Section 6 provides concluding remarks.

§2 Background

There are three main research streams regarding the solution to the IEC user's fatigue problem: (1) the discrete fitness value input method, (2) predicting the fitness method, and (3) accelerating the convergence pace of EC.

In the discrete fitness value input method, IEC users are asked to use fewer (five or seven) rating scales, instead of higher rating scales, when rating the chromosome in order to reduce their psychological fatigue. [16, 24-26]

The most popular method is to predict the fitness (values). Biles trained a Neural Network (NN) to learn non-musical melodies and used it to remove unnecessary ratings to reduce user burden. [1] Some researchers have used distance-based approaches to learn the users' fitness function [5] or to predict the individual's fitness directly to diminish the number of rating activities in each generation. [11-13, 17-18, 22]

Acceleration of EC convergence is another approach to reducing user burden. To accelerate the convergence pace of EC, Ingu and Takagi [6] proposed a new elitist. Then Takagi and his research team proposed different strategies allowing IEC users to directly participate in EC searches, easing psychological and physical fatigue. [4, 21, 23]

All three research streams have contributed to solving the fatigue problem. In this paper, we propose another approach that arises from an unsuitable search space.

§3 Customer Values-based IEC Model

The product design problem in this paper is defined as follows: A product "P" is composed of "n" attributes (P = (a_1, a_2 . . . a_n)). If attribute "a_i" has "l_i" attribute levels, then the size of the product space denoted by “S” equals “l_1 x l_2 . . . x l_n.” The IEC user (customer) is asked to search “s” (>= l) preferred product(s) from “S”.

A simple way to create the product space is to narrowly focus on obvious attributes and attribute levels. Most of the previous IEC-based design support systems created the space using this simple method, but a few researchers, Kim and Cho[7] for example, considered domain specific knowledge, resulting in a more realistic and reasonable design. We called such methods alternative-based approaches and domain knowledge-based approaches.

The above methods have been used for years in marketing research. In most cases, marketing researchers first collect data helpful in defining customers’ needs, extract main attributes and attribute levels from the data, and then define a product space according to the main attributes and attribute levels. These domain knowledge-based approaches can create “domain knowledge-based attributes and attribute levels” to determine a search space. In other cases, the product designers start with what is readily available and extract the best to create a product space. For example, “A”, “B”,… “N” are sets that contain the attributes (or attribute levels) which customers “A”, “B”,… “N” will use to make their search space. What marketing researchers or domain experts are trying to find is an intersection of set “A”, “B”,… “N”. Obviously, no one knows whether any attributes (or attribute levels) of the customers’ preferred product were filtered out or eliminated. In other words, these approaches cannot assure users that their preferred products exist in their search space. Hence, these approaches are more suitable for marketing researchers or domain experts rather than customers.

In reality, product designers in IEC are customers themselves, rather than marketing researchers or domain experts. To assure that IEC-based design systems are performing as expected, we must make sure that all customers’ preferred products exist in the search space. One of the best strategies to do this is to ensure that the search space is made up of the union set of “A”, “B”,… “N”. If this is not the case, it will result in IEC users experiencing difficulty when searching for their preferred products, and feeling boredom throughout the evolution generations. These potential pitfalls are possible causes of the fatigue problem.

To assure the search space is a complete union set for different customers, we propose building the search space using the concept of Keeney’s value-focused thinking[8-10]. The process of building the search space is as follows:

1) Develop a list of customer values.
2) Transform each value into a set of objectives, and express the objectives in a common form.
3) Organize the common form of objectives to indicate their relationships.
4) Map a relationship between objectives and attributes or attribute levels.

The first step involves asking customer, individually or in a group, what they care about in purchasing goods or services. Analysts perform the next three steps to make sense of the values identified. The initial list of values will come in many forms. Therefore, it is useful to develop some consistency in these expressions by converting each value into a corresponding objective, which is step 2. At this stage, there will likely be a long list of objectives. The first step in organizing objectives is to combine similar objectives into categories. Once objectives are categorized, it is helpful to relate categories by means-ends relationships[8]. The goal of step 3 is to reorganize means-ends relationships and articulate the fundamental (end-benefit) objectives. In step 4, we convert the objectives into product attributes and levels and show it to the customers to make sure it actually represents customers’ values.

It is expected that IEC users will effectively design interesting products by themselves throughout the evolving generations, and their "burden" will decrease when using the model with customer values-based search space. The proposed model consists of 4 modules: IEC users, database of attributes and levels, graphic user interface (GUI), and EC module. The system structure of the model is illustrated in Fig. 1.

In this paper, we call IEC systems with "customer values-based search space" the "Customer Values-based IEC Model" and IEC systems with "domain knowledge-based search space" the "Domain Knowledge-based IEC Model." IEC users follow the procedures below to design their products with either system:

1) The system selects the attribute levels at random, combines them into a set of candidate products as the initial population, and displays it to the IEC user.

2) The IEC user assigns fitness to all the candidate products.

3) EC module performs the selection, crossover or mutation operations according to the fitness of the candidate products, and generates the next new population. Repeat steps (2) and (3) until the preferred products emerge or the other end condition is reached.

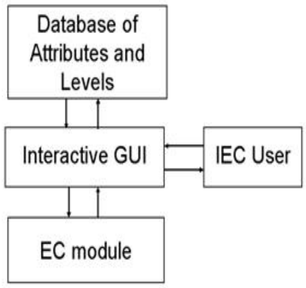

Fig.1 System structure of the proposed model

§4 Case Study

We used mineral water bottle design as a case to explore the anti-fatigue capability of users utilizing the proposed model. A mineral water bottle is divided into 5 parts (attributes): cap, neck, label, body, and base (Fig. 2); each part can take on any level or variation of values. We developed two different systems, a domain knowledge-based IEC system (IEC_DK) and a customer values-based IEC system (IEC_CV), to support the subjects designing their preferred mineral water bottle.

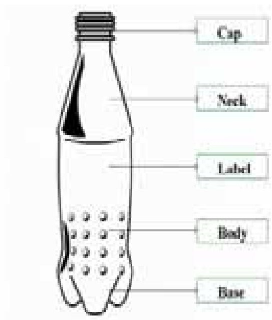

Fig. 2 Five parts of a mineral water bottle

4.1 Solution Space of the Domain Knowledge-based System

To create the solution space of the domain knowledge-based system, we first collected all possible kinds of mineral water bottles on the market, discussed with domain experts to decide attribute levels for each part, and then encoded the bottles with 2, 3, 3, 3, 3 bits for each part. Each part has an attribute name, such as attribute cap, attribute neck, etc.

The chromosome structure of the domain knowledge-based system and the phenotype of the encoded parts are shown in Fig. 3 (including the portions outside the red line). The size of the solution space is 2^{14}. The subjects were asked to search for their preferred bottle out of 16,384 candidates with the supports of IEC_DK.

4.2 Solution Space of the Customer Values-based System

To establish a customer values-based search space to meet customer values, we followed value-focused thinking and the four steps in Section 4.1. We first held three brainstorming sessions to gather the customer values. Ten to fifteen people were invited to participate in the brainstorming sessions, and each session lasted between 2 and 3 hours. All participants were randomly selected from EMBA students and employees from different companies.

Fig. 3 The genotype and phenotype of the mineral water bottle

At the beginning of each brainstorming session, we clarified the purpose of the meeting and asked participants to write down their possible needs or wants when purchasing bottled mineral water. We then engaged them in a discussion regarding these needs or wants in order to generate additional values that should be added to the value list.

Once the brainstorming session stopped producing additional values, we combined the individual lists following Keeney's suggestions. Ideally, this comprehensive list should include the values necessary to describe any individual's needs or wants.

We converted each value into a corresponding objective, and then combined similar objectives into categories. Once objectives are categorized, we must identify these objectives as means objectives or fundamental objectives. Tables 1 and 2 are partial groups of fundamental objectives and means objectives for mineral water bottles. In order to create an effective search space, we invited a marketing expert and a product designer to create an initial set of attribute levels according to the objectives listed in Tables 1 and 2. After revision by the brainstorming participants, the final set of attributes was decided.

The chromosome structure of the customer values-based system and the phenotype of the encoded attribute levels are shown in Fig. 3 (including all). The size of the solution space is 2^{19}. The subjects were asked to search for their preferred bottle out of 524,288 candidates.

Table 1 Partial groups of fundamental objectives related to mineral water bottles

A. Overall Objective
- A1. Maximize user satisfaction

B. Maximize Product Quality
- B1. Maximize design quality of color scheme
- B2. Maximize design quality of graph lines or grains
- B2. Maximize design quality of appearance molding

C. Maximize product practicability
- C1. Maximize easily grasp the bottle
- C2. Maximize portability
- C3. Maximize volume of bottle
- C4. Maximize drink convenience
- C5. Maximize easily open the bottle

D. Maximize Safety
- D1. Avoid dangers when opening the cap
- D2. Maximize air tightness
- D3. Avoid bottle toppling and falling
- D4. Avoid causing pollution inside the bottle

E. Maximize product creativity
- E1. Maximize variety molding
- E2. Maximize diversity design
- E3. Maximize product added value

F. Maximize enjoyment
- F1. Maximize driving force for willing to drink water
- F2. Maximize flavor effects

G. Minimize Environment Impact
- G1. Maximize return rates of empty bottle
- G2. Minimize environment pollution
- G3. Maximize resource re-usage

Table 2 Partial groups of means objectives related to mineral water bottles

B1. Maximize design quality of color scheme	C2. Maximize portability
a. Mountain and river patterns	a. Hook or ring on neck
b. Water waves pattern	b. Retractable body
c Water drops pattern	c. Handful stem on neck
d. Snowflakes pattern	d. Ring on cap
e. Snowman pattern	C4. Maximize drink convenience
B2. Maximize design quality of graph lines or grains	a. Double caps
a. Transparence Color	b. Make scales on body
b. Ice blue color	c. …
c. Diversity colors	

§5 Experiments

We developed 2 systems, IEC_DK and IEC_CV, to verify anti-fatigue capability and system efficiency. All systems ran on Pentium PCs with the same specifications. For each experiment, the population size was set to 8, one-point crossover was used, one elitist individual in each generation was preserved in the next generation, and the crossover rate and mutation rate were 0.6 and 0.08, respectively. Rating all strategy was used to rate 8 bottles on a 9-point scale in every generation. Fig. 4 is a snapshot of IEC_CV.

Fig. 4 Snapshot of the IEC_CV system

5.1 IEC User's Burden Test

The IEC user's burden test contains two subtests: the fatigue index (or endurance) test and the satisfaction test. The fatigue index test shows significant differences in the endurance of a subject using the different systems. The satisfaction test tells which system the subject's preferred bottle came from.

In the fatigue index test, subjects were asked to do their best to create their preferred bottle with no time limitations or any generation limitations. In other words, they could run the system as long as they wanted until they rated any bottle at 9 points. We took the number of generations the subject used as the fatigue index to measure the subject's endurance. For example, if subject A spent 12 generations to design bottles, we set the fatigue index of subject A equal to 12. If fatigue index of subject A (randomly selected) was 20 when using IEC_CV to create his or her preferred bottle, while the fatigue index of subject B (randomly selected) was 10 when using IEC_DK (and if the situation or environment had not changed since they ran the systems), then we can say that subject A ran IEC_CV with more endurance than subject B ran IEC_DK. But more endurance not means effectively reduced burden, if we wish for an effective evidence to confirm the reduce burden happened, we need a further test to assure the subjects will more satisfied with the bottles form IEC_CV.

The randomly selected 70 subjects were separated into groups CV and DK, with 35 subjects in each group. None of the subjects participated in any previous brainstorming sessions for gathering customer values. Every subject in group CV was assigned to run IEC_CV individually, and every subject in group DK was assigned to run IEC_DK.

The results of the Sign test on the fatigue index are shown in Table 3. Eighty percent of the paired samples are negative differences (IEC_DK < IEC_CV), and the results suggest that there is a statistically significant difference between IEC_CV and IEC_DK ($p < .001$).

Table 3 Results of the Sign test on the fatigue index

Frequencies

		N
IEC_DK- IEC_CV	Negative Differences [a]	29
	Positive Differences [b]	5
	Ties [c]	2
	Total	36

a. IEC_DK <IEC_CV b. IEC_DK >IEC_CV c. IEC_DK =IEC_CV

Test Statistics[a]

	IEC_DK - IEC_CV
Z	-3.944[a]
Asymp. Sig. (2-tailed)	.000

a. Signed Test

Table 4 Results of the Wilcoxon Signed Ranks Test on satisfaction scores

Ranks

		N	Mean Rank	Sum of Ranks
IEC_DK - IEC_CV	Negative Ranks	28[a]	18.73	524.50
	Positive Ranks	5[b]	7.30	36.50
	Ties	2[c]		
	Total	35		

a. IEC_DK < IEC_CV b. IEC_DK > IEC_CV c. IEC_CV = IEC_DK

Test Statistics[b]

	IEC_DK - IEC_CV
Z	-4.361[a]
Asymp. Sig. (2-tailed)	.000

a. Bassed on positive ranks b. Wilcoxon Signed Ranks Test

At end of each test, every subject was asked to choose one bottle as his or her preferred bottle, and was asked to rate the preferred bottle on a 100-point scale to get a satisfaction score. The results of the Wilcoxon signed ranks test on satisfaction score are shown in Table 4. These results indicate that the subjects were more satisfied with the bottles from IEC_CV, and IEC_CV is statistically significantly different from IEC_DK ($p < .001$).

From the above results, we can say that because IEC_CV effectively reduces the subject's burden, the subject is willing to spend more time and expend more effort in searching for his or her preferred product.

5.2 Efficiency Test

In Section 5.1, we mentioned that high fatigue index means low burden, but that is not true for an efficiency system. Following the example in Section 5.1, if subject A spent 20 generations to design the preferred bottle with IEC_CV, subject B was only willing to spend 10 generations to design the preferred bottle with IEC_DK. Yet if IEC_DK is more efficient than IEC_CV, we cannot say that subject B felt more burden than subject A. In other words, only testing the IEC user's burden is not enough to judge whether a system has decreased the user burden.

If we can make sure the fatigue index of IEC_CV is higher than IEC_DK, and the efficiency of IEC_CV is higher than (or is equal to) IEC_DK, then we have enough confidence to say IEC_DK can decrease user burden. In this section, we provide evidence showing the system efficiency of the proposed IEC_CV is higher than IEC_DK.

One week after the IEC user's burden test, we randomly selected 30 subjects from the previous 70 subjects and asked each of them to run IEC_CV and IEC_DK in random sequence. To compare system efficiency, each subject was asked to choose his or her preferred product in 10 generations. In other words, after 10 generations each subject (S_i) must have his or her preferred bottle from IEC_CV, P_{CVi}, and their preferred bottle from IEC_DK, P_{DKi}.

The last step of the test was to ask each subject (S_i) to compare P_{CVi} with P_{Dki} by rating each on a 100-point scale, and choosing the highest one as the most preferred bottle. We collected 30 most preferred bottles; 25 of them were generated from IEC_CV, and only 5 bottles were from IEC_DK. The Wilcoxon signed-rank test for two paired samples results are shown in Table 5; the difference between P_{CVi} and P_{DKi} is significant ($p < 0.05$).

Since IEC_CV performed better than IEC_DK in both the user burden test and the system efficiency test, we believe that IEC_CV is helpful in decreasing user burden.

Table 5 Results of the Wilcoxon Signed Ranks Test on system efficiency

Ranks

		N	Mean Rank	Sum of Ranks
$P_{DK} - P_{CV}$	Negative Ranks	25[a]	15.19	395.00
	Positive Ranks	5[b]	20.20	101.00
	Ties	0[c]		
	Total	30		

a. $P_{DK} < P_{CV}$ b. $P_{DK} > P_{CV}$ c. $P_{DK} = P_{CV}$

Test Statistics [b]

	$P_{DK} - P_{CV}$
Z	-2.886[a]
Asymp. Sig. (2-tailed)	.004

a. Based on positive ranks b. Wilcoxon Signed Ranks Test

§6 Concluding Remarks

The fatigue problem and customer design are interesting issues in IEC. It is a good strategy to use IEC as a core technology for customer design because we believe that one of the primary causes of the fatigue problem in customer design is that the customers' preferred product does not exist in the search space. If we cannot assure that the customers' preferred product exists in the search space, the customers will suffer fatigue, and it will be difficult to generate their preferred product with IEC. Based on that concept, we proposed a customer values-based IEC model to solve the fatigue problem. A case study, designing mineral water bottles, was used to verify the proposed system.

We developed two IEC-based systems, one with a customer values-based search space and the other with a domain knowledge-based search space. We conducted IEC user burden tests and system efficiency tests over a two-week period. The results of the case study imply that providing a complete union set of attribute levels as a search space is helpful in reducing user burden. To further confirm the concept that "the right search space can reduce users' burden in IEC", more case studies and comprehensive tests with large groups of different subjects are needed.

The fundamental contribution of this paper is to point out the importance of an appropriate search space to fatigue problem research. To ensure that users are searching on a complete search space, we proposed a process following Keeney's value-focused thinking. What we proposed is simply a starting point, however, and there are many operations, such as how to create customer values, how to translate the values into a set of users' objectives, how to map the objectives to attributes and its levels, etc., that need further refinement to guarantee an appropriate search space.

The search spaces of IEC_CV are always larger than those of IEC_DK, and the large search space is detrimental to the convergence speed of the IEC. Parmee et al.[19] introduced the framework for an experimental interactive evolutionary design system (IEDS), which provides users' preference information to the design team during the interaction procedures in IEC. Using IEDS, the design team can understand the overall problem domain in terms of relevant objectives, constraints, and variable ranges. The design team or IEDS can then further redefine the design space, perhaps by the inclusion or removal of objectives. Changes concerning the relative importance or the reduction of variable ranges are expected to be helpful in speeding up convergence and discovering innovative and creative products. How to integrate IEC_CV with IEDS is also an interesting topic in solving the fatigue problem.

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