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# RUNNING SHOE DESIGN SYSTEM WITH ARTIFICIAL BEE COLONY METHOD USING GAZE INFORMATION

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## ABSTRACT

To retrieve multimodal candidate solutions for real users, we investigated the effectiveness of an interactive evolutionary computation (IEC) method with an artificial bee colony (ABC) algorithm. Using three types of bees (i.e., employed, onlooker, and scout bees), the ABC algorithm retrieves various candidate solutions. Our previous study showed the effectiveness of the IEC with the ABC algorithm while looking at various practical IEC parameters from a numerical simulation using a pseudo-user that imitates user preferences. The results showed that the IEC with the ABC algorithm could retrieve more multimodal candidates than the interactive genetic algorithm (IGA), the previous chief method of IECs. However, we did not examine the effectiveness of the IEC with the ABC algorithm for real users. In this study, we performed experiments to examine the effectiveness of the IEC with the ABC algorithm for real users using running shoe designs as an evaluation object. The investigations compared multimodal candidate solutions using the IGA method as a comparison tool, retrieving the performance of both methods. To evaluate candidates, we employed user gaze information to reduce user evaluation loads. The results showed that the evaluation time for evaluating candidates of the IEC with the ABC algorithm was shorter than that of the IGA method. Moreover, we confirmed that the IEC with the ABC algorithm could retrieve more multimodal candidate solutions than the IGA method.

***Keywords:*** *Artificial bee colony, Interactive evolutionary computation, Multimodal retrieval*

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## 1 INTRODUCTION

Internet shopping has recently gained popularity worldwide. There are numerous goods, contents, and services on the Web. Therefore, Internet users must watch various goods and use keyword retrieval to find the goods they want.

The interactive evolutionary computation (IEC) method is useful for solving such a problem. The IEC method is a technique that optimizes and retrieves candidate solutions using the Kansei information of users (Takagi, 2001). Systems using the IEC method include the music generation systems (Yamaguchi & Fukumoto, 2019) and big data searching support system (Hao et al., 2017), among many others.

IEC systems usually use a genetic algorithm (GA) for evolutionary computation (EC) operation. The GA performs a unimodal retrieval that globally searches for a single goal. However, real users have multimodal preferences for various objects (e.g., clothes and music). Hence, an IEC system must have unimodal and multimodal searching performance.

To widely search candidates, IEC systems must use an algorithm that performs multimodal searches and simultaneously retrieves candidate solutions. The multimodal retrieval can present various candidate solutions and satisfy user preferences. This method is effective for product recommendation on the Internet because it considers users' preferences multidirectionally. To apply the multimodal retrieval of candidate solutions to an IEC method, our previous studies used a parallel interactive tabu search (PITS) algorithm with multiple tabu search (TS) retrievals and a hybrid GA–TS algorithm (Domae et al., 2013; Takenouchi et al., 2019a). However, the PITS algorithm generates multiple TS retrievals simultaneously, retaining those with a higher user evaluation and deleting those with a lower user evaluation. Therefore, the PITS algorithm is complicated and cannot simply retrieve candidate solutions. The hybrid GA–TS method performs only a single TS search during GA searching. If a user has multiple preferences, this method retrieves only approximately two kinds of candidate solutions.

To address this challenge, an artificial bee colony (ABC) algorithm is applied to the IEC method for retrieving multimodal candidate solutions. The ABC algorithm is a swarm intelligence method, which effectively optimizes multivariable and multimodal functions (Karaboga, 2010). It has three types of bees, namely, employed, onlooker, and scout bees, and searches for multimodal candidate solutions using these bee collaborators. Previously, we investigated the effectiveness of the IEC with the ABC algorithm from the viewpoint of multimodal retrieving of candidates via numerical simulations with the pseudo-user that imitates users' Kansei evaluations (Takenouchi, 2021). This work showed that the IEC with the ABC algorithm could retrieve candidates more multimodal than the conventional IEC with the GA method. However, we did not investigate the effectiveness of the IEC with the ABC algorithm for real users.

Therefore, in this study, we investigate the effectiveness of the proposed system for real users using evaluation experiments that employ the proposed system with a running shoe design system. The proposed system evaluates candidate solutions using users' gaze information, which reduces user evaluation loads. The experiments examine performance comparisons with the compared system that employs the GA method.

## 2 PROPOSED SYSTEM

### 2.1 Schematic of the proposed system

Figure 1 shows a schematic of the proposed system. First, at the employed bee phase, it randomly generates the initial candidate solutions. Each employed bee randomly selects a candidate solution from the initial candidates and generates a new candidate solution. Then, a user evaluates (only views) the candidate solutions, including the initial and randomly generated candidate solutions of each employed bee. Then, the ABC algorithm compares each for each employed bee's initial candidate solution with the newly generated candidate solution. It selects a candidate solution having a high evaluation value as the selected candidate solution of the employed bee.

Next, during the onlooker bee phase, each onlooker bee uses the evaluation values of each candidate solutions to select a candidate solution with a high evaluation value and counts the number of selections for every candidate solution.

Finally, during the scout bee phase, each scout bee replaces the candidate solutions that reach the upper limit of the selections for each onlooker bee with newly generated candidate solutions. However, if there is a similar candidate solution with a similarity of 80% in the retrieving record, it regenerates new candidates. Additionally, it generates a neighboring candidate solution for each candidate solution, which is less than the upper limit. It also generates a neighboring candidate solution for retrieving records, with fewer retrieving counts. In the next generation, the system uses these newly generated candidates and neighboring candidates. Then, the system presents these new candidate solutions again and repeats the operations of the ABC algorithm.

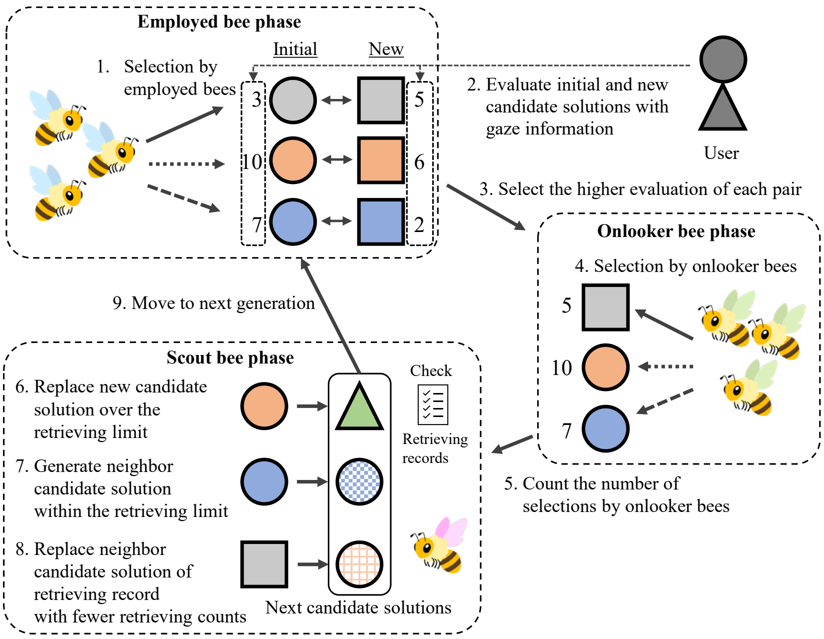


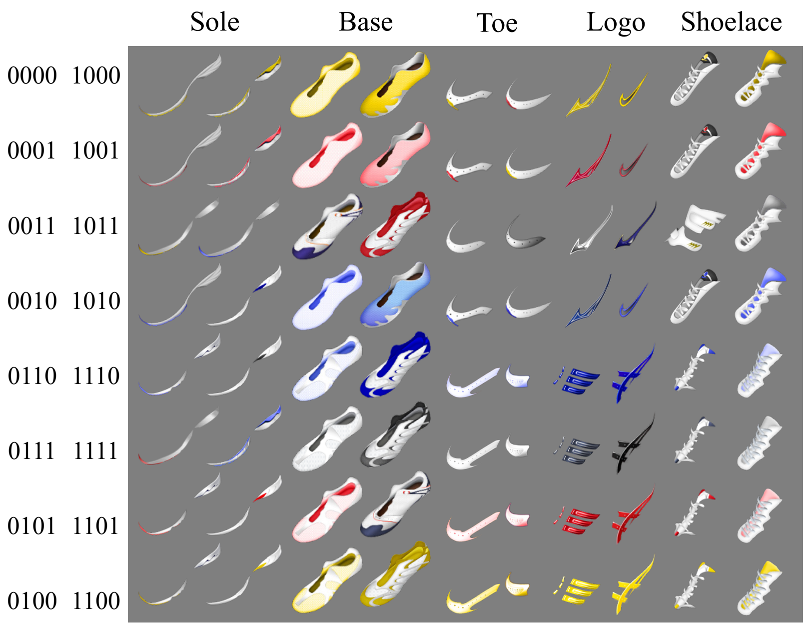

Figure 1. Schematic of the proposed system

The proposed system similar to our earlier work, evaluates candidate solutions based on user gaze information (Takenouchi & Tokumaru, 2019b). We use a Tobii Pro X2-30 (Sampling rate: 30[Hz]) eye tracker for measuring user gaze information. The proposed system counts users' gaze positions while viewing candidate solutions and uses gaze position counts to evaluate each candidate solution. The candidates with higher (lower) gaze position counts are assigned higher (lower) evaluation values.

## 2.2 Running shoe design

Figure 2 shows the gene coding of the running shoe design and part designs. The running shoe designs are identical to those in our earlier study (Takenouchi & Tokumaru, 2019a). The design consists of five parts: base, logo, shoelace, sole, and toe. Each part has 16 (= $2^4$) designs. Therefore, the gene length is 20 bits, and the proposed system can generate approximately 1 million (= $2^{20}$) designs. In Fig. 2(b), we assigned a bit pattern to each design by considering the similarity between the design appearance of each part and gene rows.


(a) Design structure




(b) Part designs

**Figure 2**. Running shoe design

### 2.3 Evaluation interface

Figure 3 shows the evaluation interface of the proposed system. The initial candidate solutions in the first generation and the higher scored candidate solutions in the previous generation after the second generation are represented by five designs on the left side of the interface. The five designs on the right side are the candidate solutions randomly generated by each employed bee.

The proposed system generates more candidates for each employed bee than the initial candidates. The number of employed bees in the proposed system is similar to the number of candidates described in Section 3.1. Therefore, the user evaluates twice the number of candidate solutions. Furthermore, in Fig. 3, the proposed system presents 10 designs regardless of the number of the generations.

After completing the evaluations, the proposed system presents new designs when the user clicks the arrow button at the bottom right. The user clicks the X button at the bottom left when they are finished with the system.

## 3 EVALUATION EXPERIMENTS

### 3.1 Outline of the experiments

The experiments investigated whether the proposed system can multimodally retrieve users' favorite shoe designs. A total of 16 university students (10 males and 6 females) in their 20s participated in this study. We followed the necessary procedures based on the ethical code for research related to human participants at the Fukuoka Institute of Technology. Moreover, the experiment was conducted after sufficient the subjects had been adequately informed about the procedures and we obtained their informed consent. The experiments compared the performance of the proposed and compared systems in terms their multimodal retrieval of candidates. The compared system uses the GA method as a conventional IEC system. We set the order of the system used randomly for each subject, considering the order effects.


**Figure 3**. Evaluation interface

**Table 1**. Experimental parameters

| | Proposed system | Compared system |
|---|---|---|
| Candidate solutions | 20 | 40 |
| Gene length | 20 bits | |
| Generations | 15 | |
| Employed bees | 20 | – |
| Onlooker bees | 100 | – |
| Retrieval limits | 10 | – |
| Selection | – | Roulette selection + elite preservation |
| Crossover | – | Uniform crossover |
| Mutation rates | 10% | |

Table 1 shows the experimental parameters. The proposed system uses twice the number of candidates (20) because each employed bee generates new candidates (20) randomly corresponding to the candidates. Then, the compared system also uses 40 candidates, considering the influence of the evolutionary performance by the number of candidates. Each subject viewed and evaluated 40 candidates in each generation in both systems. The EC operations of both systems use the candidates for the top half evaluation.

After using each system, we asked each subject to answer the following Questions A–E with three- or four- stage evaluations.

A：Did the last generation's shoe designs meet your preferences?

B：Have there been any changes in shoe designs?

C：Did the shoe designs meet your desire each time you turned the page?

D：Did you find the preferred designs, whether right or left?

E：How did you feel about the time you spent viewing designs during the evaluation?

Moreover, we took note of the subjects' comments on the system and their feelings and observations.

### 3.2 Results of the evaluation time

Figure 4 shows the results of the evaluation time for 6 subjects. The evaluation time indicates terms from showing the initial designs to clicking the X button at the 15$^{th}$ generation interface. In Fig. 4, the average evaluation time of the proposed (compared) system was approximately 421[s] (462[s]). This is because the candidates in the compared system converge on a single goal while passing the generations, making it difficult for the subjects to distinguish between the given designs. Then, the time it took to complete the evaluations for the compared system became long. Furthermore, the candidates of the proposed system converge on multiple goals, allowing subjects to quickly notice and evaluate the differences between the given designs.

### 3.3 Results of the multimodal retrieval for the generated designs

Figure 5 shows the variance in the logo presentations. The variance of the presentations for each part becomes high when the presented parts are biased. In Fig. 5, the variances of each subject for the proposed system were smaller than that those for the compared system. Therefore, the proposed system can represent various shoe designs and the compared system presents many similar designs. In particular, the variances of Subjects C and N were higher than those of the others.

Thus, the compared system cannot multimodally retrieve candidates that can satisfy each subject. The proposed system has a smaller bias of the presentations and can multimodally retrieve candidates that can satisfy each subject. We also confirmed the same tendency about the variances of any other parts.

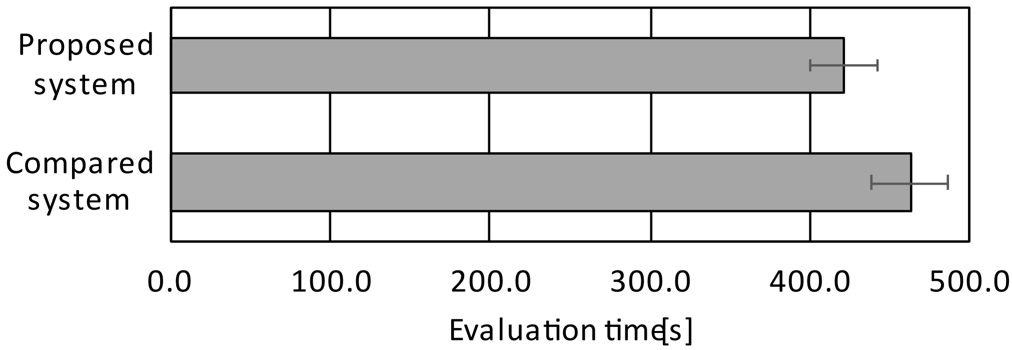



**Figure 4**. Results of the evaluation time

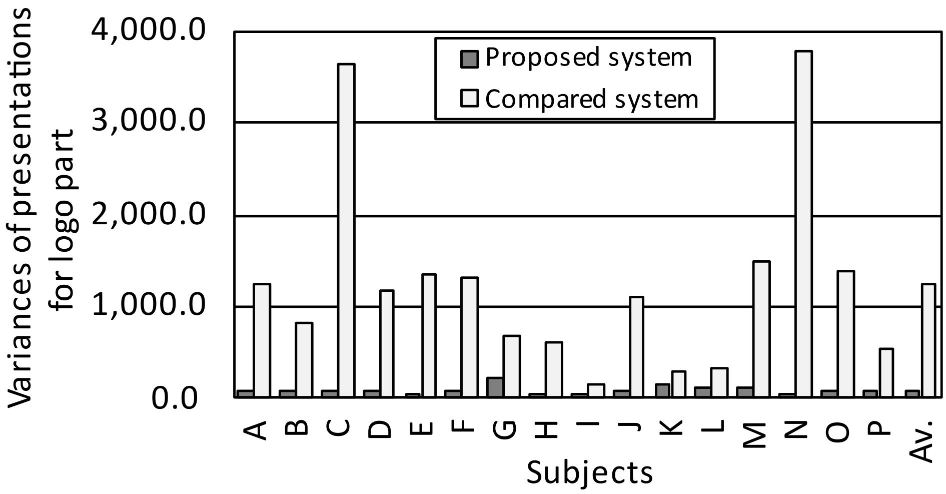



**Figure 5**. Results of the variances for the presentations

### 3.4 Results of the questionnaire

Table 2 shows the results of the questionnaires. In Tab. 2(a), in both systems, 75% of all subjects answered that they found their multiple favorite shoe designs in the last generation. Thus, both systems can present users' favorite shoe designs.

However, in Tab. 2(b), in the compared system, 69% of all subjects, including 58% of the 12 subjects who answered that they found their multiple favorite shoe designs in Question A, answered that they felt the kinds of the presented designs were small. This was caused by the subjects counting the presented shoe designs as their favorite designs. In the proposed system, 81% of all subjects answered that they found various favorite designs. Only 13% of all subjects, including 12% of the 12 subjects who answered that they found the multiple favorite shoe designs in Question A, answered that they felt that kinds of the presented designs were small. Therefore, compared with the compared system, the proposed system can present various designs.

From Tab. 2(c), in both systems, more than half of all subjects felt that each time system presented their favorite shoe designs whenever the y turned the page. Moreover, in Tab. 2(d), the number of the subjects who answered that there were several favorite designs on the left side of the interface were larger than that of the subjects who answered that there were many designs on the right side of the interface. This shows caused that the proposed system presents higher scored designs on the left side and randomly generated designs by employed bees on the right side.

In Tab. 2(e), more than half of all subjects felt that the evaluation time was longer in both systems. Both systems required each subject to evaluate 40 designs in each generation. Even if both systems employed user gaze information for evaluating candidates and each subject only viewed the presented designs, the subjects that felt the evaluation time was long.

Next, we describe the subjects' comments. First, there was a comment from some subjects that "the proposed system presents various designs" that suppose multimodal retrieval performance of the proposed system. However, some subjects expressed that "they found their favorite shoe designs, but they want to confirm more neighboring favorite designs." From the comments, we found the improvement items for the proposed system. For example, using the TS method to retrieve candidates locally, the proposed system moves some designs to the neighbors that can satisfy the users.

From all the results, we confirmed that the proposed system could generate multimodal shoe designs that can satisfy the users. Furthermore, from the perspective of the multimodal retrieval of user favorite designs, the proposed system performed better than the compared system.

## 4 CONCLUSIONS

We investigated the effectiveness of the proposed system from the perspective of multimodal retrieval of candidates for real users. The experimental results showed that the proposed system could retrieve candidates more multimodal than the compared system. The results uphold the numerical simulations' findings (Takenouchi, & Tokumaru, 2021). In future research, we will improve the proposed system with more details and test its multimodal retrieval effectiveness.

**Table 2**. Results of the questionnaire

(a) Question A

| | Found multiple designs | Found a single design | Not found |
|---|---|---|---|
| Proposed system | 75% | 19% | 6% |
| Compared system | 75% | 19% | 6% |

(b) Question B

| | Quite a lot | A lot | Few | Very few |
|---|---|---|---|---|
| Proposed system | 25% | 56% | 19% | 0% |
| Compared system | 0% | 31% | 50% | 19% |

(c) Question C

| | Found multiple designs | Found a single design | Not found |
|---|---|---|---|
| Proposed system | 56% | 38% | 6% |
| Compared system | 63% | 31% | 6% |

(d) Question D

| | Right designs | Left designs | Same |
|---|---|---|---|
| Proposed system | 13% | 56% | 31% |
| Compared system | 25% | 38% | 38% |

(e) Question E

| | Very long | A little long | A little short | Very short |
|---|---|---|---|---|
| Proposed system | 6% | 75% | 19% | 0% |
| Compared system | 0% | 63% | 32% | 6% |

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