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Bacterial Foraging for Product Color Planning

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Bacterial Foraging Algorithm (BFA) is a recently developed swarm bio-inspired algorithm mimics the foraging and chemotactic behaviors of E. coli bacteria. However, BFA's optimization performance is not so good compared with other classic algorithms as it has several shortages. This paper presents an improved BFA (IBFA). In the new algorithm, social learning is introduced so that the bacteria will tumble towards better directions in the chemotactic steps. As well, adaptive step length strategy is employed in chemotaxis to balance the exploration and exploitation abilities. The new algorithm is tested on the real-world multi-working modes products (MMP) color planning problem. Experiments present a comparative study on the color planning problem for the proposed IBFA, genetic algorithm (GA), and particle swarm optimization (PSO). Simulation results demonstrate that the proposed method is feasible and efficient.

Key words: Color Planning, Bacterial Foraging, Genetic Algorithm, Particle Swarm Optimization, Grey Theory.

Nature serves as a rich source of concepts, principles, and mechanisms for designing artificial computational systems to solve complex engineering problems. In the optimization domain, researchers have developed many effective stochastic techniques that mimic the specific structures or behaviors of certain creatures. In recent years, the computational model of the *E. coli* bacterium has attracted more and more attention, due to its research potential in engineering applications[1].

The *E. coli* is one of the earliest bacteria which have been researched. It has a plasma membrane, cell wall, and capsule that contains the cytoplasm and nucleoid. Besides, it has several flagella which are randomly distributed around its cell wall. The flagella rotate in the same direction at about 100–200 revolutions per second. If the flagella rotate clockwise, they will pull on the cell to make a "tumble." And if they rotate counterclockwise, their effects accumulate by forming a bundle which makes the bacterium "run" in one direction, as shown in Figure 1.

A few models have been developed to mimic bacterial foraging behavior and have been applied for solving some practical problems. Among them, bacterial foraging optimization (BFA) is a successful population-based numerical optimization algorithm that mimics the foraging behavior of E. coli bacteria[2]. Until now, BFA has been applied to some engineering problems, such as optimal control[3], optimal power flow[4], color image enhancement[5] and machine learning[6]. However, classical BFA algorithm suffers from two major drawbacks:

(1) As a bacterial colony evolves, the fixed run-length unit of each bacterium may lead them trap in local optima or oscillate about the optima.

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(2) There is no information sharing among the bacterial colony. Thus, experimentation with complex and multimodal benchmark functions reveals that the BFA algorithm possesses a poor convergence behavior and its performance heavily decreases with the growth of search space dimensionality and problem complexity.

In the past few decades, many artificial intelligent (AI) techniques have been applied to product color planning. Jing Sun employed the methods of back-propagation neural network and genetic algorithm to establish a decision support system for the evaluation of product color design [7]. Yu-Chuan Shen et al. proposed a linguistic-based evaluation model specified in terms of the CIE color system for evaluating the harmony characteristics of images comprising multiple colors in the interior design field [8]. All the studies above focus on color-combination images of simple products (i.e., single working-mode products). However, for many products under different working modes, the ratio, shape and space location of their color areas will be accordingly changed. With the change of working mode and color area, the images of customers for these multi-working modes product (MMP) will be changed as well.

In this work, we proposed a novel swarm intelligence search technique that mimics the bacterial foraging behaviors to solve the MMP. In stead of the simple description of chemotactic behavior in original bacterial foraging optimization (BFA) algorithm, the proposed algorithm also incorporates the adaptive search and social learning strategies.

Improved bacterial foraging algorithm

The proposed improved bacterial foraging algorithm (IBFA) system consists of three principal mechanisms, namely chemotaxis, social learning, and adaptive search. We briefly describe each of these processes as follows:

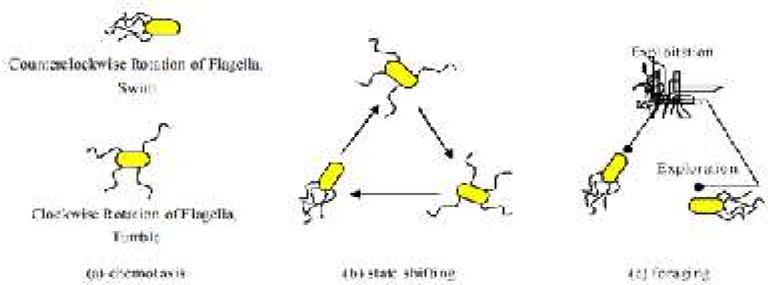

Fig. 1. Bacterial foraging behaviors

Chemotaxis

Suppose θ,(t) represents the i^{th} bacterium at t^{th} chemotactic step. $C(i)$ is the chemotactic step-size for this bacterium during each run or tumble (run-length unit). Then in each computational chemotactic step, the movement of the i^{th} bacterium can be represented as

$$\theta_i(t+1) = \theta_i(t) + C_i(t)\varphi_i(t) \qquad ...(1)$$

where $\varphi(i)$ is the direction vector of the t^{th} chemotactic step. When the bacterial movement is run, is the same with the last chemotactic step; otherwise, is a social learning vector whose elements should be calculated as in Section 2.2.

Social Learning

In our model, we assume that all bacteria can memory the best position they have reached and share the information to other bacteria. That is, a bacterium will decide which direction to tumble using the information of its personal best position and the population's global best position. Based on the assumption, the tumble directions are generated using

$$\varphi_i = (\theta_{gbest} - \theta_i) + (\theta_{i,pbest} - \theta_i) \qquad ...(2)$$

where ‚$_{gbest}$ is the global best of the population found so far and ‚$_{i,pbest}$ is the i^{th} bacterium's personal historical best.

Adaptive Search Strategy

In IBFA, we use the decreasing step length adaptive strategy. The step length will decrease with the fitness evaluations, as shown in equation (3).

$$C_i(t) = C_{start} - \frac{(C_{start} - C_{end}) \times nowiter}{totaliter} \quad \text{...(3)}$$

where C_{start} is the step length at the beginning. C_{end} is the step length at the end. *nowiter* is the current chemotactic step. *totaliter* is the total chemotactic steps. In the early stage of IBFA algorithm, larger step length provides the exploration ability. While at the later stage, small step length is used to make the algorithm turn to exploitation.

Color evaluatin model for MMP

Color-combination Evaluation in Each Working Mode

In this Section, gray clustering method is used to determine image value of color-combination for MMP in each working mode. Supposed a

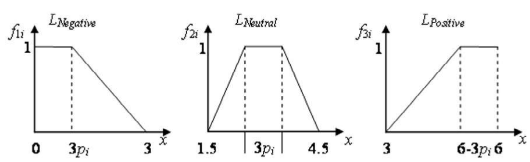

Fig. 2. Weighting factor functions of linguistic sets

product consists of n groups of components, where the components in a single group share the same color. The area of the outer surface of each group can be calculated by 3D software. The area ratio of each group can be normalized as $P = \{p_1, p_2, \ldots, p_n\}$, $p_1 + p_2 + \ldots + p_n = 1$. Then the normalized value of area p_i can be viewed as the corresponding weight of the ith group.

The membership function of each linguistic set can be transformed into the weighting factor function, which is subsequently corrected by the threshold value ΔT_i, which is defined as $\Delta T_i = 3p_i$. The corresponding weighting factor functions of the three linguistic sets, namely *LPositive*, *LNeutral*, and *LNegative*, for the ith group (or color) are illustrated in Fig. 2.

We then define the product's color set as $\Omega = \{C_1, C_2, \ldots, C_n\}$ and the clustering attribute (i.e., the linguistic sets) as $\Lambda = \{A_1, A_2, \ldots, A_m\}$, here $\Lambda = \{LPositive, LNeutral, LNegative\}$ and $m = 3$. According to gray clustering theorem, the overall evaluation for the kth attribute cluster is calculated as follows:

$$\sigma_k = \sum_{i=1}^{n} f_{ki}(\theta_i)\, p_i \quad \text{...(4)}$$

where $f_{ki}(\bullet)$ is the corresponding weighting factor functions of the kth linguistic set for the ith group (or color), p_i is the weighting factor of the corresponding group that is with the same value as the normalized area ratio, $i = 1, 2, \ldots, n$, and $k = 1, 2, \ldots, m$.

Hence, the linguistic set of color-combination scheme for the single working mode product can be constructed as $\xi = \{\sigma_1, \sigma_2, \ldots, \sigma_m\}$. Then the maximum value is selected from these m attributes of ξ as the color-combination image value of the target product of single working mode.

Color Evaluation for Multi-working Mode

When MMP alter their working modes, the area ratio of their color spaces will be accordingly changed[12]. Assume the working mode set of MMP is defined as $\Theta = \{M_1, M_2, \ldots, M_q\}$ and the color set is defined as $\Omega = \{C_1, C_2, \ldots, C_n\}$, the area ratios change according to working mode shifting can be summarized by matrix $\mathbf{P}_{q \times n}$ as follows:

$$\begin{array}{cc} & \begin{array}{cccc} 1 & 2 & \cdots & n \end{array} \\ \mathrm{P} = & \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{qn} \end{bmatrix} \begin{array}{c} 1 \\ 2 \\ \cdots \\ q \end{array} \end{array} \quad \text{...(5)}$$

As mentioned above, customers' subjective images can be changed with the variation of product working modes. In this work, color area factors are introduced into evaluation of color-combination images. The color-combination images generated in different working modes are considered as evaluating attributes, to which the corresponding weights are assigned. Then the MMP color-combination image Φ can be synthetically evaluated by:

$$\sigma_k^j = \sum_{i=1}^{n} f_{ki}^j\left(\theta_i^j\right) p_{ij} \quad \text{...(6)}$$

$$\Phi = \sum_{j=1}^{q} w_j \max_{k=1}^{m}\{\sigma_k^j\} \quad \text{...(7)}$$

where σ_k^j is color-combination image evaluating value of product in working mode j for the kth linguistic set, $f_{ki}^j(\cdot)$ is the corresponding weighting factor functions of the kth linguistic set for the ith color space in the jth working mode, θ_i^j represents the image evaluation to the ith color space in the j^{th} working mode, p_{ij} is the normalized area ratio for the ith color space in the jth working mode, w_j is normalized working time ratio of each working mode j, that is, $\sum_{j=1}^{q} w_j = 1$.

Table 1. The average image value of 125 color samples

Code	Score		Code	Score		Code	Score		Code	Score		Code	Score	
	F-M	Y-M		F-M	Y-M		F-M	Y-M		F-M	Y-M		F-M	Y-M
1	0.82	0.73	26	0.25	0.03	51	0.95	0.83	76	0.02	0.05	101	0.92	0.40
2	0.23	0.96	27	0.22	0.06	52	0.71	0.71	77	0.41	0.14	102	0.84	0.31
3	0.24	0.91	28	0.27	0.08	53	0.56	0.70	78	0.42	0.16	103	0.43	0.31
4	0.19	0.41	29	0.30	0.14	54	0.24	0.40	79	0.44	0.22	104	0.14	0.12
5	0.11	0.27	30	0.28	0.16	55	0.08	0.16	80	0.44	0.27	105	0.03	0.05
6	0.10	0.27	31	0.41	0.51	56	0.10	0.18	81	0.58	0.70	106	0.02	0.07
7	0.28	0.44	32	0.44	0.50	57	0.11	0.48	82	0.52	0.68	107	0.17	0.21
8	0.31	0.90	33	0.38	0.48	58	0.59	0.52	83	0.50	0.62	108	0.42	0.38
9	0.95	0.96	34	0.32	0.49	59	0.84	0.89	84	0.48	0.61	109	0.78	0.41
10	0.93	0.90	35	0.22	0.35	60	0.98	0.92	85	0.01	0.17	110	0.83	0.39
11	0.80	0.42	36	0.21	0.37	61	0.82	0.81	86	0.02	0.26	111	0.79	0.28
12	0.78	0.53	37	0.33	0.62	62	0.87	0.80	87	0.34	0.29	112	0.71	0.23
13	0.77	0.56	38	0.9	0.88	63	0.50	0.78	88	0.54	0.47	113	0.64	0.18
14	0.54	0.58	39	0.83	0.84	64	0.27	0.57	89	0.81	0.48	114	0.46	0.19
15	0.27	0.34	40	0.87	0.85	65	0.02	0.28	90	0.85	0.56	115	0.02	0.14
16	0.33	0.27	41	0.98	0.94	66	0.03	0.31	91	0.91	0.63	116	0.01	0.05
17	0.47	0.43	42	0.96	0.92	67	0.61	0.62	92	0.87	0.66	117	0.42	0.12
18	0.48	0.34	43	0.30	0.87	68	0.59	0.47	93	0.45	0.43	118	0.72	0.11
19	0.51	0.32	44	0.36	0.61	69	0.66	0.52	94	0.13	0.21	119	0.73	0.21
20	0.55	0.37	45	0.38	0.26	70	0.69	0.51	95	0.01	0.06	120	0.77	0.23
21	0.41	0.08	46	0.41	0.11	71	0.72	0.46	96	0.07	0.03	121	0.53	0.15
22	0.42	0.11	47	0.35	0.45	72	0.71	0.34	97	0.11	0.18	122	0.51	0.14
23	0.38	0.12	48	0.23	0.86	73	0.63	0.22	98	0.67	0.46	123	0.49	0.12
24	0.29	0.04	49	0.69	0.89	74	0.51	0.12	99	0.78	0.75	124	0.47	0.08
25	0.21	0.13	50	0.96	0.98	75	0.12	0.15	100	0.96	0.86	125	0.50	0.38

Table 2. The rank list of 10 schemes from IBFA, PSO and GA

Rank	1	2	3	4	5
Scheme	No.1	No.4	No.3	No.7	No.2
Fitness	0.0421	0.0520	0.0488	0.0506	0.0511
Algo.	IBFA	IBFA	IBFA	IBFA	PSO
Rank	6	7	8	9	10
Scheme	No.8	No.6	No.9	No.10	No.5
Fitness	0.0515	0.0510	0.0510	0.0511	0.0601
Algo.	GA	PSO	GA	PSO	PSO

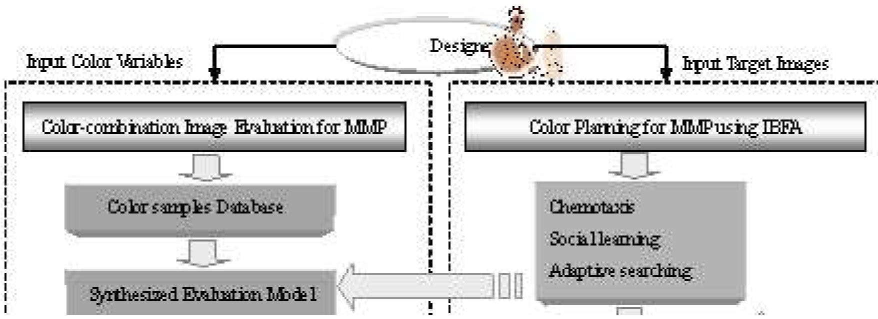

Fig. 3. The algorithmic framework of MMP color planning based on IBFA

Fig. 4. 3-D model of the hair-drier

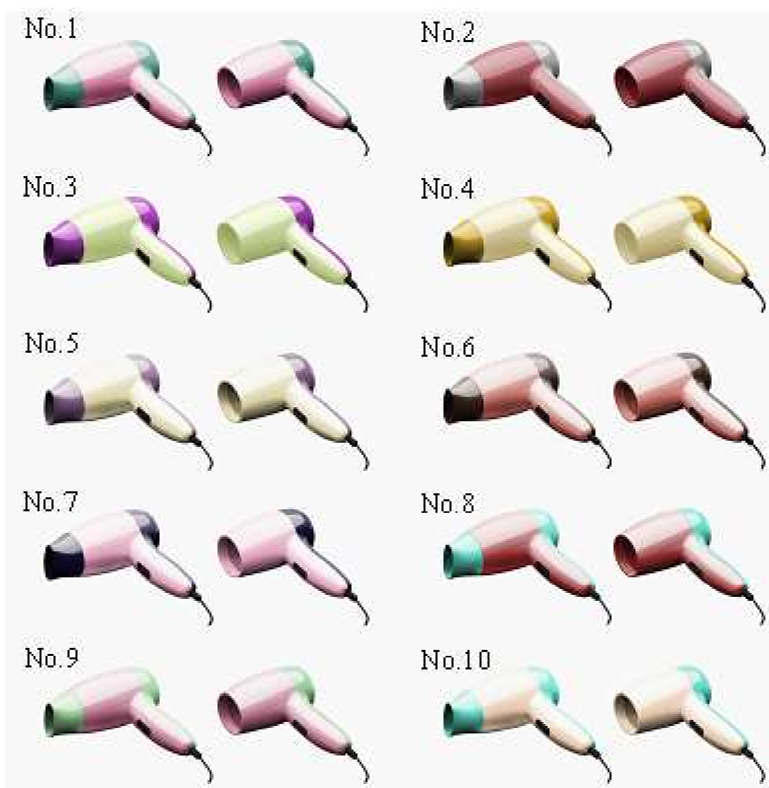

Fig. 5. Top 10 optimal results.

Color planning for mmp based on IBFA

The detailed design of MMP Color Planning algorithm based on IBFA is introduced in this section.

MMP Color Planning Procedure

The overall operating process, which can be depicted in Fig.3, is described as follows:

Initialization Phase

Create Basic Single-color Samples

Initially, a basic single-color samples database should be constructed to evaluate color-combination of MMP. In this work, the basic color samples are produced by regularly adjusting its constituent RGB parameters. According to the target studying product, these color samples should be rendered on the 3D model of this product and evaluated by selected peoples in the design field. Then, given the desired image words, the average scores of image evaluation for these color samples can be obtained.

Population Generation

N individual forming the IBFA population, each of which is regarded as a color combination candidate for MMP, should be randomly generated in the searching space. Each individual is characterized by real number representation and has a dimension equal to 3*M*. Here *M* is the number of used colors of the target product and every *M* dimensionalities represent the RGB parameters of one used color. The *i*th bacterium of the colony is defined as follows:

$$X_i = (x_i^1, x_i^2, \ldots, x_i^{3M}), \quad x_i^j \in [0, 255] \quad \ldots(8)$$

For example, a real-number individual [128.55, 192.33, 128.78 255.21 128.11 0.56], which should be normalized to [129, 192, 129, 255, 128, 1], is a possible planning solution of a two-color product. The 1 to 3 bit of the normalized solution means that the RGB parameters of the first color are 129, 192, and 129, respectively; while the 4 to 6 bit of the normalized solution means that the RGB parameters of the second color are 255, 128, and 1, respectively.

Optimization Phase

At the end of the initialization phase, all the information needed for the optimization phase is obtained for generating the optimal MMP color planning solution. The basic building blocks of this phase are:

Fitness Evaluation

For each bacterium X_i , namely each color planning solution candidate, its color-combination image evaluation of multi-working mode can be calculated by Eqn. 1-8. Accordingly, at every iteration, the fitness of each bacterium *i* can be calculated as:

$$Fitness_i = \sum_{\tau=1}^{\omega} \eta_\tau \left|\Phi_i^\tau - \hat{\Phi}^\tau\right|, \quad \sum_{\tau=1}^{\omega} \eta_\tau = 1 \quad \ldots(9)$$

where ω is the number of used image word, η is the weight of image word, Φ^τ_i is color-combination evaluating value for image word τ, Φ^τ is the required color-combination evaluating value for image word of the target MMP.

Population Evolution

Compare the evaluated fitness values and perform the chemotaxis, self-adaptation, reproduction, and elimination dispersal for each bacterium to update its position.

Termination condition

The computation is repeated until the maximum number of iteration is met or the satisfied color-combination of the target product is obtained.

EXPERIMENTAL

In this section, an illustrative MMP example with 2-colors areas and two working modes is conducted to validate the effectiveness and efficiency of MMP color planning based on the proposed image evaluation model and bacterial foraging algorithm that compared with particle swarm optimization (PSO) and genetic algorithm (GA).

In this case, the effectiveness and feasibility of the proposed color planning method is demonstrated by taking the case of a multi-working modes product, namely the hair-drier, for illustration purposes. A rendered 3-D model of the hair-drier was shown in Fig. 4, I was the special working mode; II was the common working mode. Two arbitrary colors were assigned to the primary components of the hair-drier: color1 was assigned to the body, while color2 was to the nozzle and air filter. The two designed colors could be exchanged by adjusting the RGB parameter values at random. 125 color samples were created by regularly adjusting the RGB parameters with a constant equi-gap of 64 units within the range of 0–255. 125 color samples for testing were generated by regularly adjusting the constituent RGB parameters with a fixed equi-gap of 64 units within the range of 0-255. Then the 125 color samples were successively rendered on the 3-D model and shown in the form of photo images to the research subjects to perform a questionnaire investigation on a LCD monitor. 32 opposite linguistic word pairs which described the color images of hair-drier were collected. Then two linguistic word pairs which were mostly used at the time of purchasing were selected by the sales person of hair-drier as image words in the case study: Female-Male (F-M) and Young-Mature (Y-M).

60 subjects were invited to fill out questionnaires by giving their personal image perception ranked from 0 to 1. 0 denoted female/young image perception, 0.5 denoted neutral image perception, and 1 denoted male/mature image perception. The average image evaluation values obtained of 125 product color samples versus two image word pairs were shown in Table1.

The initialized population size and the maximum generation for IBFA, GA and PSO are 50 and 1000 respectively. According to marketing survey, the coefficients in the fitness function in this experiment are set as: ¸ is equal to F-M and Y-M, *i* is mode I and mode II respectively, $E_{F\text{-}M} = 0.3$, $E_{Y\text{-}M} = 0.4$; $W_{F\text{-}M}$=0.5, $W_{Y\text{-}M}$=0.5, W_{I}=0.5, W_{II}=0.5.

To clearly illustrate the MMP color planning results by all the algorithms, Fig. 5 shows the top 10 optimal color-combination schemes with the fitness values obtained by GA, PSO, and IBFA. Then 30 subjects are invited to sort these 10 color-combination schemes that illustrated in Fig. 5 in accordance with how these solutions fit the target image. The rank result is shown in Table 2, .form which we see clearly that most obtained MMP color combination schemes from IBFA are ranked ahead of PSO and GA.

CONCLUSIONS

This work proposed a novel bacterial foraging algorithm combining chemotaxis, social learning, and adaptive search strategy. And an optimization model for color planning of multi-working mode products is developed to assist designers in efficiently grasping image preferences of consumers. This work then applied IBFA algorithm to solve the MMP color planning problem. The simulation result shows that the solutions of IBFA for the product color-combination searching are more acceptable than both GA and PSO, in terms of optimization accuracy and computation robustness, and are closer to people's image preference.

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