

Research Article

Multi-Working Modes Product-Color Planning Based on Evolutionary Algorithms and Swarm Intelligence

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Received 27 September 2009; Accepted 5 March 2010

Academic Editor: Ben T. Nohara

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In order to assist designer in color planning during product development, a novel synthesized evaluation method is presented to evaluate color-combination schemes of multi-working modes products (MMPs). The proposed evaluation method considers color-combination images in different working modes as evaluating attributes, to which the corresponding weights are assigned for synthesized evaluation. Then a mathematical model is developed to search for optimal color-combination schemes of MMP based on the proposed evaluation method and two powerful search techniques known as Evolution Algorithms (EAs) and Swarm Intelligence (SI). In the experiments, we present a comparative study for two EAs, namely, Genetic Algorithm (GA) and Difference Evolution (DE), and one SI algorithm, namely, Particle Swarm Optimization (PSO), on searching for color-combination schemes of MMP problem. All of the algorithms are evaluated against a test scenario, namely, an Arm-type aerial work platform, which has two working modes. The results show that the DE obtains the superior solution than the other two algorithms for color-combination scheme searching problem in terms of optimization accuracy and computation robustness. Simulation results demonstrate that the proposed method is feasible and efficient.

1. Introduction

Color plays an important part in determining the appeal of a product to its potential customers. With the replacement of different colors, the individuals' requirements of different customer groups can be satisfied. More and more companies have realized that color planning is essential to the success of a new product. However, it is difficult to effectively determine how people perceive and evaluate color-combination image in various products.

Thus most product-color planning issues are still based on the personal experience and estimation. Thus the effective product-color planning methods are needed to be executed in order to assist product designers to implement their color planning strategies.

In the past few decades, many techniques have been applied to product-color planning problem. Lai et al. presented an approach of user-oriented design for transforming users' perception into product elements design using Quantitative Theory Type I and neural networks [1]. Tsai et al. proposed a rapid conceptual design approach, which creates color-rendered forms and combines parameter-based features with fuzzy neural network theorems and gray theory to predict their image evaluation [2]. Lin presented a design method for product form and color by using neural networks, fuzzy logic, and tabu search [3]. 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 [4]. Ma et al. applied fuzzy analytic hierarchy process and image compositing technique to construct the design decision-making support system provided for choosing the optimum product-color [5]. Tokumaru et al. proposed a system to automatically compose color schemes which are in harmony with a color input in the system and correspondent to user's image [6]. Tsai et al. presented a color design system which enables the designer to evaluate color image or to search for required color combinations using gray theory and genetic algorithm [7–9]. Zhang developed a product-color intelligent design system based on G. Birkhoff aesthetics model MS theory, psychophysical field theory, as well as genetic and immunity theory [10]. Wang developed a computer-aided color design system composed of color selection, color harmony, color scheme, and color assistant database, which is based on the cooperation CAXA [11].

All of the studies above focus on color-combination images for simple products. However, for many products under different working conditions or modes, the ratio, shape and space location of their color areas will be accordingly changed, as shown in Figure 1. With the change of product mode and color area, the images of customers for these multi-working modes product (MMP) will be changed as well. Therefore, above image evaluating methods in the literatures for product-color-combination cannot apply to MMP because of the color areas changing issue.

In order to provide assistance to designers in color planning for MMP, a novel synthesized evaluation model, which is an evaluation principle of the computer-aided product-color planning system, is created in this paper to evaluate color-combination image for MMP. This method considers each color-combination image under different working modes as evaluation attribute, to which the corresponding weight is assigned for synthesized evaluation.

In the past few decades, nature-inspired computation has attracted significant attention. Among them, the most successful are Evolutionary Algorithms (EAs) and Swarm Intelligence (SI). Evolutionary algorithms are search methods that take their inspiration from natural selection and survival of the fittest in the biological world. Swarm intelligence is an innovative computational way inspired by the collective behavior of social systems. Due to their simplicity and flexibility, various EAs and SI methods have been developed to solve many real-world engineering problems [12–14]. In existing studies of color planning, one type of EAs methods, namely, the Genetic algorithm (GA), has been employed to the searching of optimal color scheme [7–10]. Although GA illustrated marked performance in solving the color planning problem in these studies, the comparative studies between GA and other EA or SI techniques are desired to find more efficient and effective color planning algorithms.



Figure 1: Multi-working modes products.

This paper investigates the applicability of the following three different nature-inspired algorithms in the color planning for MMP: two Evolutionary algorithms, namely, the Genetic Algorithm (GA) and the Difference Evolution (DE), and one Swarm Intelligence algorithm, namely, the Particle Swarm Optimization (PSO). All of the algorithms are evaluated against a test scenario, namely, an arm-type aerial work platform, which has two working modes. The simulation results, which are focusing on minimizing the specific objective function that represents the mathematical model of the color planning problem for MMP, are reported in this paper to show the performance comparison of the three nature-inspired algorithms.

The rest of this paper is organized as follows. In Section 2, we will give the briefly reviews of GA, DE, and PSO algorithms. The implementation methods and procedures are described in Section 3, including the Experimental sample construction, the questionnaire investigation, the synthesized evaluation method, and the search model for MMP color planning based on Evolutional Algorithms and Swarm Intelligence. In Section 4, the comparative study is performed for the three nature-inspired algorithms on solving the MMP color planning problem. Finally, Section 5 outlines the conclusions.

2. Description of the Algorithms

This paper employs Genetic Algorithm, Difference Evolution, and Particle Swarm Optimization to search for the color-combination schemes that will closely satisfy the requirements of the multi-working modes products. These three population-based algorithms, which are conceptually simple and easy to implement, have considerable potential for solving complex real-world optimization problems.

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Set  $t := 0$ ;
INITIALIZE. Randomize an initial population  $P(t)$ ;
WHILE (the termination conditions are not met)
  Select  $P(t + 1)$  from  $P(t)$  using roulette wheel selection;
  Crossover  $P(t + 1)$  using intermediate recombination;
  Mutate  $P(t + 1)$ ;
  Set  $t := t + 1$ ;
END WHILE

```

Algorithm 1: Pseudocode of the GA algorithm.

2.1. Genetic Algorithm

The discovery of genetic algorithms (GAs) was dated to the 1960s by Holland and further described by Goldberg [15]. GA is population-based optimization method that employs the mechanics of natural selection, namely, mutation, recombination (or crossover), reproduction, and selection. The mutation process perturbs a candidate solution randomly; the recombination process mixes the current solutions to generate the new ones; the reproduction process replicates the most successful solutions found in the population; the selection process purges poor solution from the population. GA has been successfully adopted in many complex optimization problems and shows its merits over traditional optimization methods, especially when the system under study has multiple local optimum solutions.

GA evolves a population of candidate solutions; each of which is usually coded as a binary string called a chromosome. The fitness of each chromosome is then evaluated using an objective function after the chromosome has been decoded. Upon completion of the evaluation, a biased roulette wheel is used to randomly select pairs of better chromosomes to undergo such genetic operations as crossover and mutation that mimic nature. Should the newly produced chromosomes turn out to be stronger than the weaker ones from the previous generation, they will replace these weaker chromosomes. This evolution process continues until the stopping criteria are reached. Just like in nature, the best individuals survive and are able to transmit their genes to the next generations.

A real-coded GA uses a vector of floating-point numbers instead of binary codes for implementing chromosome encoding. The crossover operator of a real-coded GA is constructed by borrowing the concept of linear combination of vectors from the area of convex set theory. The random mutation operator proposed for real-coded GA operates on the gene by introducing into it a perturbation in the feature's domain. In this paper, the real-coded GA is implemented to solve the color planning problem. The pseudocode for the GA is listed in Algorithm 1.

2.2. Differential Evolution

Differential evolution is a population-based parameter optimization technique originally proposed by Price [16]. In DE model, new individuals are generated by mutation and DE's crossover, which cunningly uses the variance within the population to guide the choice of new search points.

DE/rand/1/exp scheme is recommended to be the first choice when trying to apply differential evolution to any given problem [16]. This particular version is adopted in our work, which is briefly described as follows. For a minimization problem, DE starts to work with a population of N candidate solutions, that is, \vec{x}_i^t , $i = 1, 2, \dots, N$, where i indexes the population and t is the current generation.

For the mutation operation, a perturbed vector \vec{v}_i^t is generated according to

$$\vec{v}_i^t = \vec{x}_{r1}^t + F(\vec{x}_{r2}^t - \vec{x}_{r3}^t) \quad (2.1)$$

with random indexes $r1, r2, r3 \in \{1, 2, \dots, N\}$ and a scaling factor $F \in [0, 2]$.

For the crossover operation, the perturbed vector $\vec{v}_i^t = [v_{i1}, v_{i2}, \dots, v_{iD}]$ and target vector $\vec{x}_i^t = [x_{i1}, x_{i2}, \dots, x_{iD}]$ both are used to generate a trial vector $\vec{x}_i^{t'} = [x'_{i1}, x'_{i2}, \dots, x'_{iD}]$:

$$x'_{ij} = \begin{cases} v_{ij}, & \text{if } \text{rand } b(j) \leq \text{CR or } j = \text{rand } r(i), \\ x_{ij}, & \text{if } \text{rand } b(j) \geq \text{CR and } j \neq \text{rand } r(i), \end{cases} \quad (2.2)$$

where $j \in [1, D]$, $\text{rand } b \in [0, 1]$ is the j th evaluation of a uniform random number generator, $\text{CR} \in [0, 1]$ is the crossover constant. $\text{Rand } r(i) \in [1, 2, \dots, D]$ is a randomly chosen index which ensures that $\vec{x}_i^{t'}$ gets at least one parameter from \vec{v}_i^t .

For selection operation, a greedy scheme is performed:

$$\vec{x}_i^{t+1} = \begin{cases} \vec{x}_i^{t'}, & \text{if } \Phi(\vec{x}_i^{t'}) < \Phi(\vec{x}_i^t), \\ \vec{x}_i^t, & \text{otherwise,} \end{cases} \quad (2.3)$$

where $\Phi(\cdot)$ represents a fitness function.

2.3. Particle Swarm Optimization

The canonical PSO is a population-based technique, similar in some respects to evolutionary algorithms except that potential solutions (particles) move rather than evolve through the search space. The rules (or particle dynamics) that govern this movement are inspired by models of swarming and flocking [17]. Each particle has a position and a velocity, and experiences linear spring-like attractions towards the following two attractors.

- (i) Its previous best position.
- (ii) Best position of its neighbors.

In mathematical terms, the i th particle is represented as $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ in the D -dimensional space, where $x_{id} \in [l_d, u_d]$, $d \in [1, D]$, and l_d, u_d are the lower and upper bounds for the d th dimension, respectively. The rate of velocity for particle i is represented as

$v_i = (v_{i1}, v_{i2}, \dots, v_{iD})$ and is clamped to a maximum velocity V_{\max} which is specified by the user. In each time step t , the particles are manipulated according to the following equations:

$$\begin{aligned} v_{id}(t) &= \chi(v_{id}(t-1) + R_1 c_1 (p_{id} - x_{id}(t-1)) + R_2 c_2 (p_{gd} - x_{id}(t-1))), \\ x_{id}(t) &= x_{id}(t-1) + v_{id}(t), \end{aligned} \quad (2.4)$$

where R_1 and R_2 are random values between 0 and 1, c_1 and c_2 are learning rates, which control how far a particle will move in a single iteration, p_{id} is the best position found so far of the i th particle, p_{gd} is the best position of any particles in its neighborhood, and χ is called constriction factor, given by

$$\chi = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|}, \quad (2.5)$$

where $\varphi = c_1 + c_2$, $\varphi > 4$.

3. Implementation Methods and Procedures

The effectiveness and feasibility of the proposed color planning method is demonstrated by taking the case of a multi-working modes product, namely, the arm-type aerial work platform, for illustration purposes. Arm-type aerial work platform shortens or extends its arm according to working height. As shown in Figure 2, in the off-working mode, jib 2 and jib 3 contract into jib 1; while in the working mode, jib 2 and 3 extend out to meet the operating requirements. This paper considers two commonly used working modes of GTBZ-30, namely, off-working mode and 15 m height working mode (working mode for short).

In Figure 2, two arbitrary colors are assigned to the primary components of the aerial work platform by adjusting the RGB parameter values at random. Color-1 (R1,G1,B1) is assigned to rotary table, jib 1, and working platform, and color-2 (R2,G2,B2) is assigned to chassis, jib 2, and jib 3.

3.1. Constructing Experimental Samples

125 color samples for testing are generated by regularly adjusting the constituent RGB parameters with a fixed equigap of 64 units within the range of 0–255 (see Figure 3). These 125 color samples are successively rendered on the 3D model in order to perform the questionnaire investigation in Section 3.2 (an example of single color rendered aerial work platform model is shown as in Figure 4).

3.2. Questionnaire Investigation

Reference [18] applied principle component analysis to reduce the 30 image words to a few factors. Generally, 30 pairs of opposite image words, which are listed in Table 1, can be used to describe the color images of the aerial work platform. In this work, by means of principal

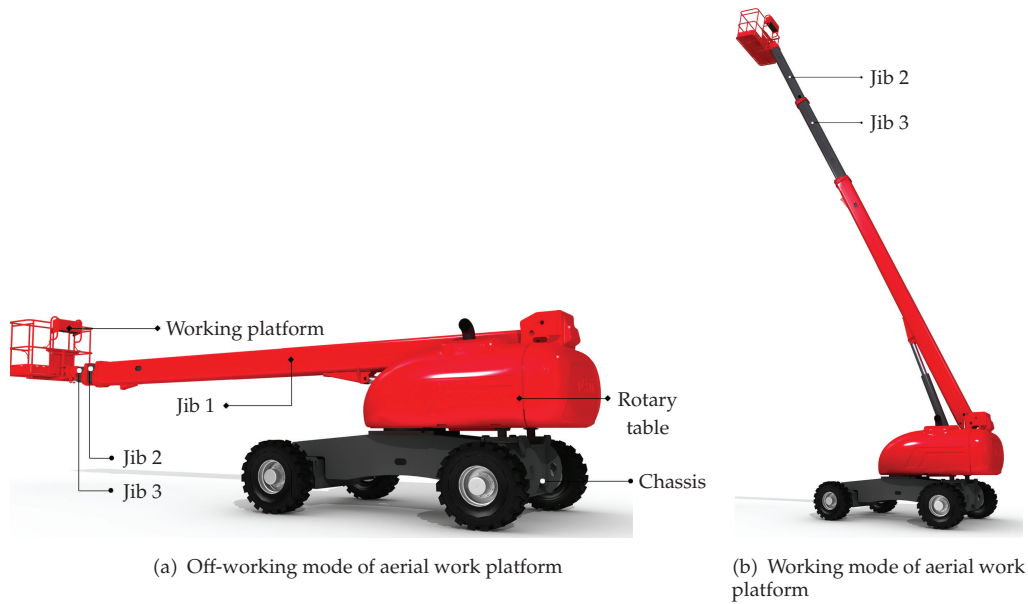


Figure 2: 3D model of arm-type aerial work platform.

Table 1: 30 pairs of opposite image words for describing the color images of the aerial work platform.

Male-Female	Simple-Complex	Young-Mature	Bright-Dark	Rough-Detailed
Cool-Warm	Particular-Popular	Expanded-Shrunken	Beautiful-Ugly	Light-Heavy
Soft-Hard	Ponderous-Deft	Favorite-Bothersome	Pleasant-Sad	Firm-Fragile
Fast-Slow	Dynamic-Static	Fashionable-Traditional	Clean-Dirty	Valued-Cheap
Lively-Solemn	Strict-Loose	Luxury-Unadorned	Excited-Quiet	Elegant-Vulgar
Faint-Striking	Emotional-Rational	Harmonious-Disharmonious	Relaxed-Tense	Strong-Weak

component analysis, two selected image word pairs, namely, Faint-Striking (F-S) and Light-Heavy (L-H), are employed.

125 product-color samples are used for questionnaire investigation and each sample is presented against a white background expect for sample 125. 120 students (74 males and 46 females) following design-related courses are invited to fill out questionnaires by giving their personal preferences that ranked from 0 to 1. For F-S, 0 denotes an entirely faint image perception, 0.5 denotes a neutral image perception, and 1 denotes an entirely striking image perception. The average image evaluation values obtained of 125 color samples versus two image pairs are shown in Table 2.

3.3. Synthesized Color-Combination Image Evaluation Method for MMP

As mentioned above, customers' subjective images can be changed with the variation of product working modes. In this paper, color area factors are introduced into evaluation of color-combination images. The color-combination images generated in different working

Table 2: The average value of 125 color samples versus two image pairs.

Code	Score		Code	Score		Code	Score		Code	Score		Code	Score	
	F-S	L-H		F-S	L-H		F-S	L-H		F-S	L-H		F-S	L-H
1	0.74	1	26	0.78	0.15	51	0.62	0.84	76	0.02	0.01	101	0.93	0.65
2	0.07	0.98	27	0.57	0.19	52	0.45	0.83	77	0.07	0.04	102	0.68	0.62
3	0.48	0.92	28	0.32	0.20	53	0.52	0.80	78	0.11	0.09	103	0.67	0.60
4	0.85	0.84	29	0.47	0.23	54	0.74	0.72	79	0.29	0.13	104	0.87	0.51
5	0.91	0.54	30	0.88	0.24	55	0.41	0.43	80	0.54	0.19	105	0.95	0.20
6	0.71	0.51	31	0.33	0.77	56	0.41	0.40	81	0.32	0.36	106	0.56	0.18
7	0.66	0.86	32	0.29	0.71	57	0.37	0.82	82	0.26	0.33	107	0.41	0.21
8	0.08	0.87	33	0.28	0.72	58	0.34	0.85	83	0.10	0.28	108	0.48	0.32
9	0.02	0.90	34	0.27	0.74	59	0.39	0.87	84	0.12	0.23	109	0.63	0.33
10	0.86	0.89	35	0.34	0.53	60	0.86	0.88	85	0.12	0.11	110	0.90	0.36
11	0.73	0.83	36	0.40	0.48	61	0.32	0.78	86	0.24	0.26	111	0.75	0.26
12	0.59	0.81	37	0.14	0.80	62	0.17	0.77	87	0.13	0.25	112	0.57	0.22
13	0.12	0.78	38	0.07	0.85	63	0.30	0.75	88	0.18	0.28	113	0.18	0.21
14	0.27	0.75	39	0.82	0.87	64	0.08	0.72	89	0.43	0.37	114	0.08	0.17
15	0.58	0.55	40	0.76	0.84	65	0.15	0.30	90	0.58	0.39	115	0.15	0.15
16	0.47	0.52	41	0.06	0.97	66	0.04	0.26	91	0.82	0.70	116	0.04	0.03
17	0.48	0.69	42	0.33	0.95	67	0.03	0.48	92	0.64	0.68	117	0.06	0.07
18	0.37	0.72	43	0.17	0.92	68	0.07	0.51	93	0.31	0.38	118	0.17	0.12
19	0.46	0.76	44	0.78	0.88	69	0.30	0.52	94	0.34	0.28	119	0.36	0.15
20	0.51	0.79	45	0.68	0.50	70	0.42	0.56	95	0.55	0.19	120	0.47	0.16
21	0.92	0.26	46	0.96	0.54	71	0.51	0.27	96	0.92	0.21	121	0.64	0.17
22	0.65	0.23	47	0.80	0.82	72	0.29	0.25	97	0.73	0.70	122	0.36	0.11
23	0.38	0.23	48	0.69	0.85	73	0.21	0.22	98	0.43	0.72	123	0.14	0.07
24	0.61	0.22	49	0.52	0.91	74	0.12	0.12	99	0.59	0.75	124	0.04	0.04
25	0.97	0.21	50	0.03	0.94	75	0.28	0.10	100	0.84	0.74	125	0.90	0

modes are considered as evaluating attributes, to which the corresponding weights are assigned. The product-color-combination image can be synthetically evaluated by

$$\Phi = \sum_{i=1}^n w_i \varphi_i, \quad (3.1)$$

where Φ is synthesized image evaluating value of product-color-combination, i is product working mode, φ_i is color-combination image evaluating value of product in working mode i , w_i is weighting value of product in working mode i , and $\sum_{i=1}^n w_i = 1$.

According to [19], gray relational generating operation is used to calculate the image evaluating value for unspecified colors which are excluded from the 125 basic color samples listed in Figure 3. Then the gray clustering operation in [19] is adopted to evaluate color-combination image evaluating value φ_i . The case study in this paper takes visible area of the aerial work platform in Figure 2 as a standard, and defines the area ratio of two colors as P . $P_O = (P_{OA}, P_{OB}) = (0.8, 0.2)$ and $P_W = (P_{WA}, P_{WB}) = (0.7, 0.3)$. Then the threshold values of the weighting factor functions are $\Delta T_{OA} = 3 \times 0.8 = 2.4$, $\Delta T_{OB} = 3 \times 0.2 = 0.6$, $\Delta T_{WA} = 3 \times 0.7 = 2.1$, and $\Delta T_{WB} = 3 \times 0.3 = 0.9$. The diagrams of the weight functions are illustrated in Figure 5.

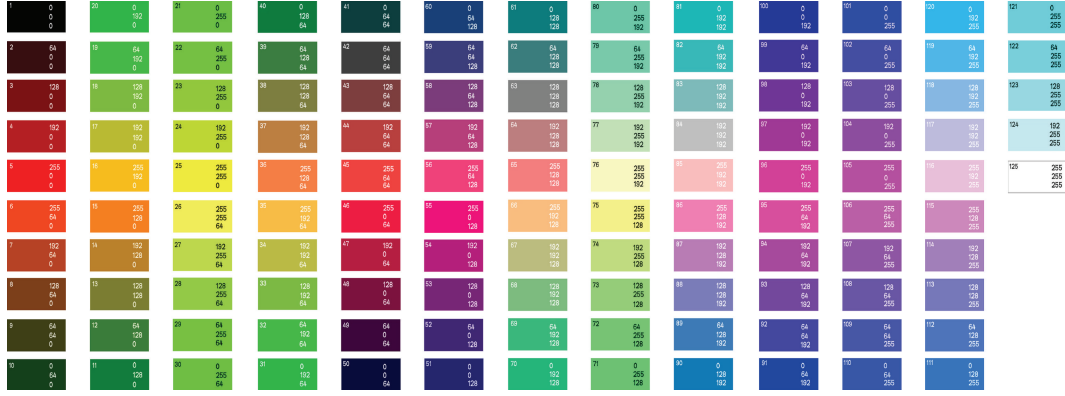


Figure 3: 125 basic color samples and corresponding RGB values.



Figure 4: One example of single color rendered aerial work platform model.

3.4. Search Model for MMP Color Planning

As described in Section 3.3, the output of the proposed MMP color evaluation model can be supplied to the fitness function of the optimization algorithms when searching for the color-combination schemes to satisfy the required product image. Accordingly, the fitness function is defined as

$$\text{Fitness} = \sum_{\theta=1}^m W_{\theta} \left| \sum_{i=1}^n w_i \varphi_i - \varphi_T \right|, \tag{3.2}$$

where θ is image index, W_{θ} is weight of image, i is working mode index, w_i is weighting value of product in working mode i , φ_i is color-combination image evaluating value of product in working mode i , φ_T is the required target image value of product-color-combination,

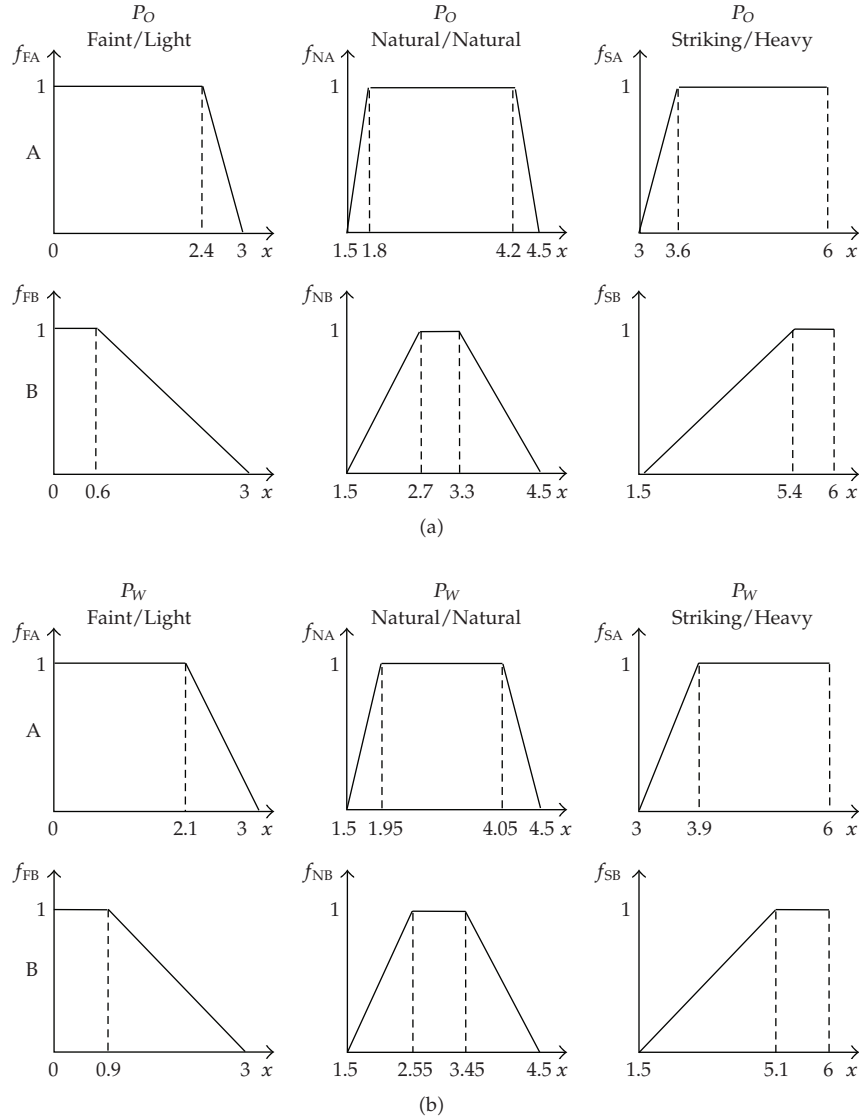


Figure 5: The diagrams of the weighting factor functions.

$W_\theta, \varphi_i, \varphi_T, \omega_i \in [0, 1]$, $\sum_{\theta=1}^m W_\theta = 1$, and $\sum_{i=1}^n \omega_i = 1$. Based on (3.2), the lower the fitness value is, the more closely the color-combination scheme fits the required color-combination image goal. However, designers have little experience or information in most of color design projects. Thus, the linguistic qualitative indicator φ_i can be considered as a fuzzy valve; accordingly, (3.2) can be expanded as

$$\text{Fitness} = \sum_{\theta=1}^m W_\theta \left| \sum_{i=1}^n \omega_i \tilde{\varphi}_i - \varphi_T \right|, \quad (3.3)$$

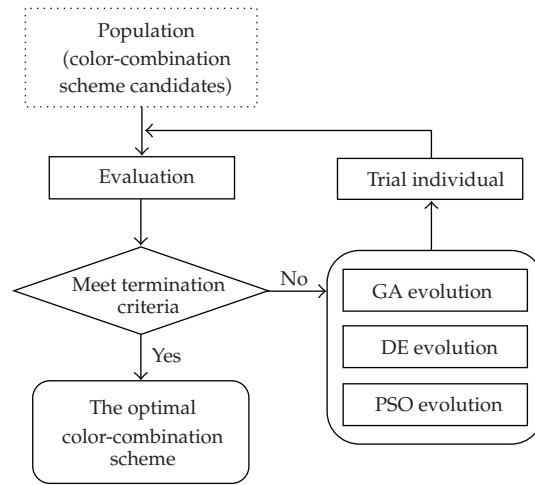


Figure 6: The flowchart of GA-, DE-, and PSO-based color-combination scheme searching algorithm.

Table 3: The statistical results of DE and GA run 100 trails.

		GA	DE	PSO
Fitness	Best	0.0501	0.0497	0.0501
	Worst	0.0872	0.0581	0.0872
	Average	0.056	0.0519	0.056
Standard Deviation		0.0079	0.0020	0.0109

where $\tilde{\varphi}_i$ is fuzzy image evaluation value of product-color-combination. The flowchart of the EI- and SI-based color-combination searching scheme is shown in Figure 6.

4. Experimental Results

In this section, GA, DE, and PSO algorithms are employed to deal with the searching for color-combination schemes of the aerial work platform issue.

The coefficients in the fitness function in this experiment are set as follows: θ is equal to F-S and L-H, accordingly i is the Off-working mode and the Working mode, respectively, $E_{F-S} = (0.85, 0.9, 0.95)$, $\lambda = 0.01$, $E_{L-H} = (0.75, 0.8, 0.85)$, $\lambda = 0.01$; $W_{F-S} = 0.5$, $W_{L-S} = 0.5$, $W_O = 0.5$, and $W_F = 0.5$.

The initialized population size and the maximum generation for each algorithm are 100 and 200, respectively. For GA, it uses one-point crossover and Gaussian mutation with the crossover rate $pc = 0.9$ and mutation rate $pm = 1/6$ (i.e., $1/\text{number of variable}$). For DE, $CR = 0.5$, and $F = 0.7$. For PSO, the learning rates c_1 and c_2 were both 2.05 and the constriction factor $\chi = 0.729$. The statistical results from 100 runs for $E_{F-S} = 0.9$, $E_{L-H} = 0.8$ are shown in Table 3.

From the results, the best, worst, and average fitness values obtained by DE in the 100 runs are better than those of GA and PSO. The standard deviation obtained by DE is smaller than those of GA and PSO. That is, DE is more robust than GA and PSO in solving the MMP color planning problem.



Figure 7: Top 10 optimal results of GA and corresponding fitness values.



Figure 8: Top 10 optimal results of DE and corresponding fitness values.

To clearly illustrate the obtained color-combination schemes, Figures 7–9 show the top 10 optimal color-combination schemes with the fitness values obtained by GA, DE, and PSO, respectively.

To further analyze the performance obtained by GA, DE, and PSO, 40 subjects (20 males and 20 females) are invited to sort these 30 color-combination schemes from Figures 7–9 according to how they fit the target image. The rank result is also shown in Table 4. From Table 4, most schemes from DE are ranked ahead of GA and PSO (especially the top 2 schemes are all obtained by DE). Thus, the results of DE are closer to people's image preference than GA and PSO.



Figure 9: Top 10 optimal results of PSO and corresponding fitness values.

Table 4: The rank list of 30 schemes from GA, DE, and PSO.

Rank	Scheme	Fitness	Rank	Scheme	Fitness	Rank	Scheme	Fitness
1	B6	0.0502	11	C7	0.0508	21	C10	0.0512
2	B7	0.0502	12	A6	0.0505	22	B5	0.0502
3	A3	0.0503	13	C5	0.0507	23	C2	0.0505
4	B9	0.0503	14	C9	0.0511	24	C8	0.0509
5	B8	0.0503	15	B2	0.0500	25	B1	0.0497
6	A5	0.0504	16	B4	0.0501	26	A2	0.0503
7	C3	0.0505	17	A7	0.0505	27	A1	0.0501
8	A8	0.0506	18	A4	0.0503	28	B10	0.0504
9	C6	0.0507	19	C4	0.0507	29	C1	0.0504
10	B3	0.0500	20	A9	0.0507	30	A10	0.0507

Generally, the lower the fitness value is, the more closely the color-combination scheme fits the required color-combination image goal. However, from Figures 7–9 and Table 4, we can see that there are some differences between the rank of fitness values and the rank of designers and customers. That is, the solutions with better fitness are not necessarily preferable in the view of designers and customers. On one hand, due to different people that have different evaluation criteria, it is difficult to construct a fitness function that can accurately describe and evaluate people's feeling of specific color-combination schemes. Therefore, the aim of this study is to find out potentially better color-combination schemes, and to offer them to the designers or customers for selection.

5. Conclusions

In order to exactly grasp image preferences of consumers to product-color-combination images and assist designers in color planning, this study has proposed a product-color

planning method for MMP based on evolutionary and swarm-intelligence-based methods. A synthesized evaluation method is created in this paper to evaluate color-combination images for MMP, which considers color-combination images under different working modes as evaluating attributes. This paper then investigates the application of three EA- and SI-based algorithms, namely, the GA, DE, and PSO algorithms, to tackle the MMP color planning problem. A case study of the two-colored aerial work platform is provided to demonstrate the effectiveness of proposed MMP color planning method. The simulation results show that the DE can find potentially better color-combination schemes than the other two algorithms.

Acknowledgment

Support of Program for New Century Excellent Talents in University of China (NCET-05-0285) is gratefully acknowledged.

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