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REGULAR RESEARCH PAPER

A discrete bio-inspired metaheuristic algorithm for efficient and accurate image matting

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Abstract

With the development of digital multimedia technologies, image matting has become one of the most popular research problem in academic field and been widely applied in industrial communities. The key challenge of image matting is how to extract the foreground region (target region) from a given image accurately. Sampling-based image matting technology implements matting by sampling some foreground pixels and background pixels from known regions and finding the best foreground–background sample pair for every undetermined pixel. The best foreground–background sample pair represents the true foreground and background colors of the corresponding undetermined pixel and they can estimate the region of this undetermined pixel accurately. Therefore, the quality of matting depends on whether the best sample pair can be found. This search process can be regarded as a combinational optimization problem. In this paper, in order to obtain more accurate matting result, we applied a bio-inspired metaheuristic algorithm to solve this problem, which is based on the promising earthworm optimization algorithm (EWA). By analyzing the property of this optimization problem, we upgrade two reproductions and the cauchy mutation of EWA to discrete calculations. The proposed algorithm is called as the discrete earthworm optimization algorithm (D-EWA). By comparing with existing optimization algorithms on a standard benchmark dataset, the experimental results show that the proposed D-EWA can obtain more accurate matting results on both visual effect and quantitative metric.

Keywords Image matting · Sample optimization problem · Earthworm optimization algorithm · Discrete calculation

1 Introduction

Image matting originated from photograph and filmmaking [1,17]. It refers to the problem of extracting foreground regions (target regions) from a given image or a video sequence, and combining these regions onto a new background region. This inverse procedure is known as image composting, as shown in Fig. 1. According to different image characteristics, current image matting techniques can be generally classified into the blue screen matting and the natural image matting [18]. In this paper, we mainly focus on the natural image matting.

In the natural image matting technology, the image is regarded as the composition of two layers: the foreground layer F and background layer B. The target of matting is to determine full pixels belong to the foreground layer. Usually, the judgment is based on a linear combination equation [14], where every pixel's color can be represented by the linear combination of a foreground pixel's color and a background pixel's color. The mathematical expression is shown below.

$$I = \alpha F + (1 - \alpha) B \tag{1}$$

where I is the color of the current pixel, which can be obtained from the image directly. F and B is the foreground color and the background color, respectively. The value of α is defined as the current pixel's foreground opacity, which is called as the alpha matte. Its values lie in [0, 1]. If $\alpha = 1$, it indicates that the current pixel is the foreground pixel. If $\alpha = 0$, it indicates that the current pixel is the background

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Fig. 1 Image matting and image composting

pixel. The task of image matting is to find the true foreground color and background color for every undetermined pixel and determine the region of the corresponding undetermined pixel accurately by expression (1). For an RGB image, I, B and F all have three color channels. Therefore, there are seven unknowns when determining the region of an undetermined pixel. Obviously, image matting is a under-constrained and ill-posed problem.

In order to obtain accurate matting result, various image matting methods have been proposed. The major categories are: propagation-based methods [2,8,14] and sampling-based methods [5,7,9,11,16]. As we have discussed above, image matting is a under-constrained and ill-posed problem. Therefore, the user input and the prior assumptions are needed in process of determining every undetermined pixel's region. Usually, the user input can be obtained by the scribbles or the trimap, which divide the given image into three regions: the known foreground region, the known background region and the undetermined region. Propagation-based methods usually use the scribbles to implement image matting. They assume that neighboring pixels are correlated under some local image statistics and propagate the alpha matte from known regions towards unknown region by using this correlation. If the given image does not meet the assumption, the performance of propagation-based methods will degrade.

Comparing with propagation-based methods, sampling-based methods attempt to find the true foreground color and background color for every undetermined pixel, instead of making certain assumption. They usually use the trimap as the user input. In the trimap, the true foreground color and background color of every undetermined pixel can be found in unknown regions. In order to reduce the time cost and improve the efficiency of image matting, early methods are based on local sampling [5,11,16]. These methods usually sampling some representative pixels from the nearby known regions of the undetermined pixel and boundary to construct sample set, and then search the best foreground–background sample pair by considering color, spatial or probabilistic characteristics of the given image. The experimental results show that they can obtain high-quality matting effect. However, due to the limitation of the regions of sampling and the number of samples, the true foreground–background colors may be missed in sample set. If the true foreground–background colors are missed, the performance of these local sampling-based methods will degrade. In order to avoid missing the true foreground–background colors, later, the global sampling method is proposed to sampling all pixels around the boundary of the known regions and undetermined region. This global sample set is huge enough to make sure that the true foreground–background colors of every undetermined pixel will be sampled in established sample set. However, how to find the true foreground–background colors for every undetermined pixel become another key issue. Usually, the number of undetermined pixels is also very huge, such as a high resolution image. Therefore, the process of searching the true foreground–background colors for every undetermined pixel in sample set is a large-scale sample optimization problem. In order to balance the time cost and performance, a random search algorithm was used in [7] to search the true foreground–background colors. The random search algorithm is a fast approximate method, which contains two steps: propagation and random search. The role of these two steps is to search the true foreground–background colors of each undetermined pixel by randomly searching in the neighboring area. The radius of neighboring area will decrease exponentially in the search process. Therefore, the random search algorithm can converge to high-quality area. By comparing with local sampling-based methods, the global sampling methods with the random search algorithm [7] can obtain more accurate matting results. However, the robustness is not enough. The true foreground–background colors are not always found because of the property of random. Recently, metaheuristic algorithms [9] have been proposed as a kind of promising search algorithm to solve the sample optimization problem. By utilizing population information and bio-inspired search strategies, metaheutistic algorithms can be more stable to find the true foreground–background colors for every undetermined pixel. In this paper, inspired by the advantage of metaheutistic algorithms to solve such large-scale optimization problem, we proposed a discrete bio-inspired metaheuristic algorithm to solve the large-scale sample optimization problem. The proposed algorithm is based on the promising earthworm optimization algorithm (EWA). By analyzing the property of the sample optimization problem, we upgrade two reproductions and the cauchy mutation in EWA to discrete calculation. These modifications can help EWA find the true foreground–background colors more effectively and improve the accurate of image matting.

The remainder of this paper is organized into four sections. Section 2 defines the sample optimization problem in sampling-based methods. Section 3 describes the discrete earthworm optimization algorithm in detail. The experiments and results are given in Sect. 4. We conclude this paper in Sect. 5.

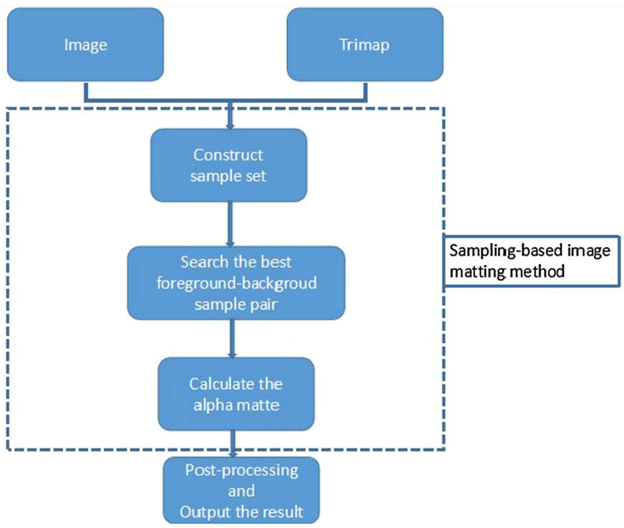

Fig. 2 The unified matting framework of sampling-based methods

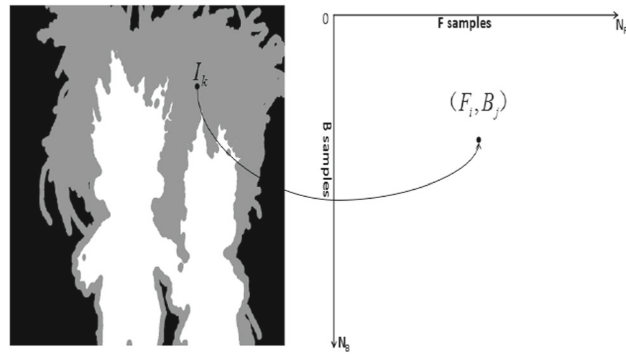

Fig. 3 Sample optimization problem. Left: The Trimap, where the white, gray and black regions represent the known foreground region, the undetermined region and the known background region, respectively; I_k is color of the kth undetermined pixel. Right: foreground–background sample pair search space, where F_i is the ith foreground sample in foreground sample set, B_j is the jth background sample in background sample set

2 The sample optimization problem in sampling-based methods

The two main operators in sampling-based image matting methods are construction of sample set and search of the best foreground–background sample pair. The first operator is carried by using a particular selection criteria to collect a subset of foreground pixels and background pixels from known regions. These collected foreground and background pixels will form the foreground sample set and background sample set. The second operator is to search the best foreground–background sample pair in sample sets for every undetermined pixel. The best foreground–background sample pair is defined as they represent the true foreground and background colors of the corresponding undetermined pixel. The unified matting framework of sampling-based methods can be constructed in Fig. 2. Assuming that the constructed foreground sample set is F and the size of F is N_F, the constructed background sample set is B and the size of B is N_B, the undetermined pixel set is I and the size of I is N_I. Once the best foreground–background sample pair is found, the alpha matte of the corresponding undetermined pixel is calculated as

$$\hat{\alpha} = \frac{(I_k - B_j)(F_i - B_j))}{\left\| F_i - B_j \right\|^2} \tag{2}$$

where I_k represents the color of the kth undetermined pixel in set I, $k = 1, 2, \ldots, N_I$; F_i represents the color of the ith pixel in foreground sample set F, $i = 1, 2, \ldots, N_F$; and B_j represents the color of the jth pixel in background sample set B, $j = 1, 2, \ldots, N_B$. Expression (2) is based on Expression (1). The calculated $\hat{\alpha}$ is used to determine whether the undetermined pixel I_k is a foreground pixel. Therefore, after constructing the foreground and background sample sets, how to find the best foreground–background sample pair for every undetermined pixel is the key optimization problem of sampling-based methods. This optimization problem is called as the sample optimization problem. For an undetermined pixel, the sample optimization problem can be regarded as a search process in two-dimensional search space, as shown in Fig. 3.

In order to find the best foreground–background sample pair for every undetermined pixel, different measures, such as the color, spatial or probabilistic characteristics of the given image, have been used to estimate the qualities of various candidate sample pairs. The most representative two measures are: color distance and spatial distance [5,7,9,11,16]. In particular, for an undetermined pixel k, we assume that the current selected candidate sample pair is (F_i, B_j), the color distance is calculated as

$$C_k(F_i, B_j) = \left\| I_k - (\hat{\alpha} F_i + (1 - \hat{\alpha}) B_j) \right\| \tag{3}$$

where $\hat{\alpha}$ is the alpha matte of the kth undetermined pixel. The color distance C_k measures how well the alpha matte $\hat{\alpha}$ calculated by expression (2) from (F_i, B_j) fit to the linear combination Eq. (1). A smaller value of C_k indicates that the estimated color of the kth undetermined pixel is more closer to the true color, and the correctness of $\hat{\alpha}$ is higher.

However, if there is an overlap in the color distribution of the known foreground and background regions, color distance cannot distinguish the true foreground color or the true background color in these regions. That is to say, a false foreground–background sample pair can also obtain a smallest value by expression (2). In order to eliminate the ambiguity of color distance, spatial distance is proposed as another measure. It is formulated as

$$S_k(F_i, B_j) = \frac{\|X_{F_i} - X_k\|}{D_F} + \frac{\|X_{B_j} - X_k\|}{D_B} \quad (4)$$

where X_{F_i} is the spatial coordinate of the ith foreground sample, X_{B_j} is the spatial coordinate of the jth background sample, and X_k is the spatial coordinate of the kth undetermined pixel. The normalization terms D_F and D_B are the nearest distance of the kth undetermined pixel to the foreground boundary and background boundary, respectively. The spatial distance measure S_k quantifies the spatial distance of the unknown pixel k to the candidate sample pair (F^i, B^j). Therefore, a smaller value of S_k indicates that the selected sample pair are spatially close to the unknown pixel.

Combining the color and the spatial measures, a classic evaluation function is proposed, which is used for estimating the quality of the candidate foreground–background sample pair for every undetermined pixel. It is defined as

$$\varepsilon_k(F_i, B_j) = C_k(F_i, B_j) + S_k(F_i, B_j) \quad (5)$$

A smaller ε_k indicates that the selected sample pair (F_i, B_j) can explain the color of the unknown pixel k well as the linear combination Eq. (1) and spatially close to this unknown pixel k. This evaluation function has been used in [7] to obtain high-quality matting effect. Therefore, we also chose it as our evaluation function.

We have introduced the definition and the evaluation function of sample optimization problem, above. Next, we will discuss the computational complexity of solving sample optimization problem. Assuming the size of undetermined pixel set, known foreground sample set and known background sample set are N_I, N_F and N_B, respectively. For an undetermined pixel, the number of candidate foreground–background sample pair is $N_F N_B$. If we search the best sample pair for every undetermined pixel one by one, the total computational complexity is $N_F N_B N_I$. Obviously, the sample optimization problem is a large-scale NP optimization problem. Its computational complexity grows with the increase of the number of the undetermined pixels and samples. Usually, the number of undetermined pixels is huge, such as a high resolution image. Besides, in order to avoid missing the true foreground colors and background colors of every undetermined pixel, the size of sample sets is also very big. Therefore, an efficient search algorithm is needed to balance the time cost and the performance. In this paper, we proposed a discrete bio-inspired metaheuristic algorithm to search the best foreground–background sample pair for every undetermined pixel. It is based on the promising earthworm optimization algorithm (EWA). In next section, we will describe in detail the proposed discrete earthworm optimization algorithm (D-EWA).

3 The discrete earthworm optimization algorithm

Earthworm optimization algorithm (EWA) as a promising metaheuristic algorithm was first proposed in [15]. It was inspired by the earthworm contribution in nature and it formulated the two kinds of reproduction behavior of the earthworms to some general-purpose search strategies. Reproduction 1 is to generate only one offspring by itself. Reproduction 2 is to generate one or more offspring at one time. According to [15], the implementation of the global search mainly depends on the Reproduction 1 and the implementation of the local search mainly depends on the Reproduction 2. Besides, the cauchy mutation (CM) is added to EWA. The experiments conducted on a suit of benchmark functions showed that the total performance of EWA is better than some popular and state-of-art metaheuristic algorithms, such as ABC [3], ACO [10], PSO [4], GA [6], DE [13] and so on. At the same time, EWA is also an encouraging method for solving discrete optimization problem [15]. In this paper, inspired by the advantage of metaheuristic algorithms to solve the large-scale optimization problem, we attempt to use the earthworm optimization algorithm to solve the large-scale sample optimization problem. Considering that the sample optimization problem is a discrete combinatorial optimization problem, we upgrade two reproductions and the cauchy mutation in EWA to discrete calculation. These modifications can help EWA more effectively find the true foreground–background colors for undetermined pixels and improve the accurate of image matting. Next, the detailed formulations of reproduction 1, reproduction 2 and cauchy mutation will be described.

3.1 Reproduction 1

As we have discussed, the sample optimization problem in sampling-based image matting method is a large-scale optimization problem, where every undetermined pixel needs to find the best foreground–background sample pair in sample pair. This is a coherent search problem. Therefore, in order to improve the efficiency of searching the best sample pair for every undetermined pixel, we use our algorithm searching the best sample pair for every undetermined pixel at the same time. In particular, if the given image has N_I undetermined pixels, the dimension of search space is $2N_I$. Every position in this $2N_I$ dimensional search space represents a candidate solution for all undetermined pixels. It is formulated as

$$X = (x_1, x_2, \ldots, x_{2N_I - 1}, x_{2N_I}) \quad (6)$$

where $x_1, x_3, \ldots, x_{2N_I - 1}$ are integers and chosen from the set $1, 2, \ldots, N_F$. They represent the indexes of selected foreground samples in foreground sample set. N_F is the size of the foreground sample set. $x_2, x_4, \ldots, x_{2N_I}$ are integers and chosen from the set $1, 2, \ldots, N_B$. They represent the indexes of selected background samples in background sample set. N_B is the size of the background sample set. A pair of adjacent odd dimensional value and even dimensional value in X represents a pair of candidate foreground–background sample pair for an undetermined pixel. That is to say, the (x_1, x_2) in X represents the candidate sample pair for the first undetermined pixel.

Our algorithm starts with randomly initializing N_P positions in $2N_I$ dimensional search space. The N_P is the size of population at every generation. Every position is an individual. Then reproduction 1 is carried out to generate offspring for every individual. It simulates the behavior that the hermaphroditic earthworm generates the offspring by itself. Therefore, in reproduction 1, every individual will generate an offspring according to its position in $2N_I$ dimensional search space. This reproduction process is formulated as

$$x1_i^j = x_{imax} + x_{imin} - \gamma x_i^j \tag{7}$$

where i represents the ith dimensional value in current individual X; j represents the jth individual in population N_P, $j = 1, 2, \ldots, N_P$. x_{imax} represents the maximum value in ith dimension; x_{imin} represents the minimum value in ith dimension. γ is a similarity factor and its range lies in [0, 1]. In reproduction 1, for the jth individual X^j, the newly-generated offspring is denoted as $X1^j$. The γ is the key factor for reproduction 1. A smaller γ can make $X1$ close to X and implement a local search around the current individual X. On the contrary, a bigger γ can make $X1$ far away from X and implements a global search in search space. In order to avoid losing the best sample pairs of all undetermined pixels, we set the γ to a bigger value to implement the global search. Moreover, considering the combinatorial optimization feature of sample optimization problem, we set the final value of γ to 1. At this point, the positions of the newly-generated offspring $X1$ and the current individual X are symmetric in search space. This operator is similar to the oppositional-based learning method [13]. The discrete calculation of the reproduction 1 is formulated as

$$x1_i^j = x_{imax} + x_{imin} - x_i^j \tag{8}$$

3.2 Reproduction 2

After executing the reproduction 1, N_P offspring $X1^1, X1^2, \ldots, X1^{N_P}$ will be generated. At this time, in order to balance the exploration and the exploitation of EWA, reproduction 2 [15] is designed for generating some offspring around the current individuals $X^1, X^2, \ldots, X^{N_P}$. This operator simulates the behavior that the earthworm can generate more than one offspring at one time. At first, two parent individuals are selected by roulette wheel selection, and we denote them as X^a and X^b, $a \neq b$ and $a, b \in \{1, 2, \ldots, N_P\}$. Then, an uniform crossover is carried out to generate the offspring $X2$. For every dimensional value of $X2$, its value is calculated as

$$x2_i = x_i^a, \quad if \ \ \text{rand} \geq 0.5 \tag{9}$$

$$x2_i = x_i^b, \quad if \ \ \text{rand} < 0.5 \tag{10}$$

where $rand$ is a random number and its value lies in [0, 1]. The reproduction 2 will be carried out N_P times and generate N_P offspring. They are $X2^1, X2^2, \ldots, X2^{N_P}$. Counting the offspring generated by reproduction 1, the total number of offspring is $2N_P$. After the implementation of the reproduction 1 and reproduction 2. The new position of every individual is calculated as

$$X^j = \beta X1^j + (1-\beta)X2^j, \ j = 1, 2, \ldots, N_P \tag{11}$$

where β is the proportional factor that adjust the proportion of the $X1^j$ and the $X2^j$. A bigger β makes the algorithm implement the global search due to the $X1^j$. A smaller β makes the algorithm implement the local search due to $X2^j$. In order to balance the exploration and the exploitation of algorithm, the β decreases with the increment of generations. It is calculate as

$$\beta^{t+1} = \lambda \beta^t \tag{12}$$

where t represents the current generation. The initial β^0 is set to 1. λ is a constant and its range lies in [0, 1]. Though the expression (12), the EWA can search the global space at the begin and mainly search the local region at the end of the search process. However, obviously, the expression (11) and the expression (12) are continuous calculations. In order to make reproduction 2 fit to the large-scale sample optimization problem, we upgrade the expression (11) and the expression (12) to discrete calculations. Due to the main functions of the expression (11) and the expression (12) are to make the new position of X^j consist of a part of the $X1^j$'s position and a part of $X2^j$'s position, this operator is similar to the crossover operator of GA [6]. Therefore, inspired by the crossover operator of GA [6], we upgrade the expression (11) and the expression (12) to two discrete calculations and achieve the same functions. The new calculation of the β is

$$\beta^{t+1} = \lfloor \lambda \beta^t \rfloor \tag{13}$$

Where the initial β^0 is set to $2N_I$. $2N_I$ is the dimension of search space. The $\lfloor\rfloor$ is a rounding operation, where the integer part of the $\lambda\beta^t$ will be hold. The β indicates how many dimensional values of $X1^j$ will pass to the new position of X^j. Once the β^t of the tth generation is obtained, the elements' orders in the set $\{1, 2, \ldots, 2N_I\}$ will be randomly reset. The first β^t elements of the reset set will be chosen as a subset S. The elements of the subset S indicates that which dimensional values of $X1^j$ will pass to the new position of X^j. The discrete calculation of the new position of X^j is

$$x_i^j = x1_i^j, \quad if\ i \in S \tag{14}$$

$$x_i^j = x2_i^j, \quad else \tag{15}$$

3.3 Cauchy mutation

To help the algorithm escape from the local optimum and improve the search ability. The cauchy mutation as an assistant operator is added in EWA. Comparing with the cauchy mutation used in [15], the discrete cauchy mutation that we proposed is based on a rounding operation. In particular, for the ith dimensional value of the jth individual in the current N_P population. The discrete cauchy mutation is given below:

$$x_i^j = x_i^j + \lfloor W_i * C \rfloor \tag{16}$$

$$W_i = \left(\sum_{j=1}^{N_P} x_i^j \right) / N_P \tag{17}$$

Where C is a random number draw from the cauchy distribution.

The main contribution of our work is to upgrade the two kinds of reproductions and the cauchy mutation of the earthworm optimization algorithm (EWA) to discrete calculations. These modifications are based on analyzing the combinatorial optimization feature of the large-scale sample optimization problem. The other steps of EWA keep in line with [15]. The detailed pseudo-code of the proposed discrete earthworm optimization algorithm (D-EWA) is shown in Algorithm 1, where the parameter $nKeep$ is introduced in [15].

3.4 The evaluation function

In the first three sections, we have discussed the detailed formulation of the proposed discrete earthworm optimization algorithm. Next, we will introduce the evaluation function that we used to search the best position in search space. As we have introduced, every position of the search space is a $2N_I$ dimensional vector, it represents a group of selected candidate foreground–background sample pairs for all N_I undetermined pixels. Therefore, the evaluation value of every position should measure the total quality of a group of candidate foreground–background sample pairs. In particular, for the jth individual in the current N_P population, its evaluation value is calculated as

Algorithm 1 The D-EWA algorithm

Input: Construct the undetermined pixel set, foreground sample set and background sample set; The sizes of these sets are denoted as: N_I, N_F and N_B, respectively. Initialize N_P individuals randomly , each with $2N_I$ dimensions in $2N_I$ search space; Each odd dimensional value of individual is chosen from the set $\{1, 2, \ldots, N_F\}$randomly. Each even dimensional value of individual is chosen from the set $\{1, 2, \ldots, N_B\}$ randomly . Set the number of generation t to 0 and the constant λ to 0.9. Initialize the value of the parameter $nKeep$. I_{max} denotes the maximum iteration number.

```
Evaluate each individual according to its position.
while t ≤ I_max do
    Sort all the individuals in ascending order according to their evaluation values.
    for j = 1 to N_P do
        Generate the offspring X1^j according to (8).
        if j > nKeep then
            Generate the offspring X2^j according to (9) and (10).
        else
            Randomly select an individual as X2^j.
        end if
        Generate the new individual X^j according to (14) and (15).
    end for
    for j = nKeep + 1 to N_P do
        Implement the cauchy mutation to X^j according to (16).
    end for
    Evaluate each individual according to its new position.
    t = t + 1.
end while
```

Output: The optimal overall individual;

$$\delta(X^j) = \sum_{i=1}^{N_I} \varepsilon_i \left(x_{2i-1}^j, x_{2i}^j \right) \tag{18}$$

This evaluation function is formed by linearly adding the evaluation value of every pair of foreground–background sample pair in the current individual X^j. The $\varepsilon_i()$ is the expression (5). Therefore, the value of this evaluation function (18) can measure the total quality of the jth individual, $j = 1, 2, \ldots, N_P$. A smaller value indicates that the current individual have more high-quality sample pairs. The position with smallest value has the best foreground–background sample pairs for all undetermined pixels. It is the best solution that we obtained by the discrete earthworm optimization algorithm.

4 Experiments and results

The experiments and the results will be discussed in this section. In this study, considering the sample optimization problem of sampling-based image matting method is large-scale combinatorial optimization problem, we attempt to design an efficient search algorithm to search the best foreground–background sample pairs for all undetermined pixels, thereby obtaining the more accurate matting effect. Inspired by the high-performance of the metaheuristic algorithm in solving the large-scale optimization, we proposed a discrete bio-inspired metaheuristic algorithm to solve the large-scale sample optimization problem. The proposed algorithm is based on earthworm optimization algorithm (EWA) [15] and can be simply called as D-EWA. Therefore, the goal of the experiment is to verify whether the proposed D-EWA can find higher-quality sample pairs for all undetermined pixel and improve the accurate of sampling-based image matting method.

In order to verify the performance of the proposed D-EWA, we chose the existing search algorithms, which have been used to solve the large-scale optimization problem, to compare. They are a random search algorithm [7] and the particle swarm optimization [9]. For avoiding missing the true foreground colors and the true background colors of all undetermined pixels, we use the global sampling method [7] to construct the sample set. All known foreground (background) pixels on the undetermined regions' boundary (the distance is 1) will be collected in the sample set. The sample optimization step will be replaced by the random search algorithm, the particle swarm optimization and the proposed D-EWA. Other steps will keep in line with the global sampling image matting method [7]. Therefore, different matting effects are produced by different search algorithms. For a fair comparison, the maximum iteration number of the particle swarm optimization and the D-EWA is set to $3 * 10^4$, which is keep in line with [9]. The size of population (N_P) is set to 50. The inertia weight and the acceleration constants of the particle swarm optimization are set to 0.7, 1.5 and 1.5, respectively. The parameters setting of the D-EWA is that $\gamma = 1$, $\lambda = 0.9$, $nKeep = 2$ and $\beta^0 = 2N_I$. N_I is the number of undetermined pixels. The maximum iteration number of the random search algorithm is $10N_I log\,(N_F N_B)$, which is keep in line with [7]. In the random search algorithm, the ratio of neighboring area decreases is set to 0.5 [7].

Fig. 4 Detailed comparisons of the 4th matting results and the 7th matting results. 1st column: the input images. 2nd column: the standard matting results. 3rd column: the matting results with the random search algorithm. 4th column: the matting results with the D-EWA

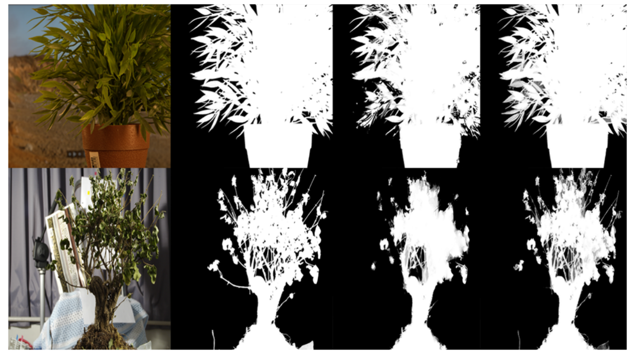

Fig. 5 Detailed comparisons of the 13th matting results and the 26th matting results. 1st column: the input images. 2nd column: the standard matting results. 3rd column: the matting results with the random search algorithm. 4th column: the matting results with the D-EWA

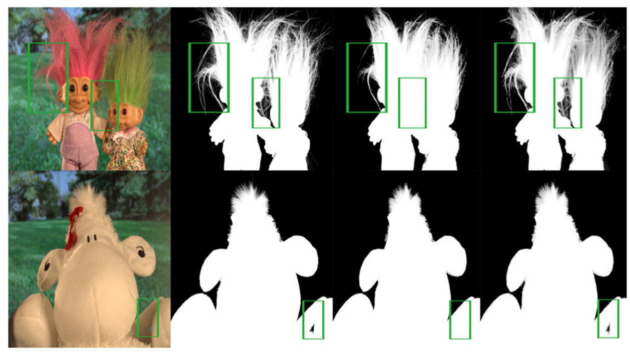

Fig. 6 Detailed comparisons of the 4th matting results and the 7th matting results. 1st column: the input images. 2nd column: the standard matting results. 3rd column: the matting results with the PSO. 4th column: the matting results with the D-EWA

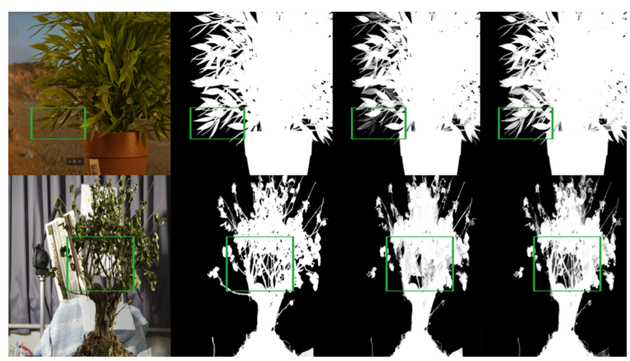

Fig. 7 Detailed comparisons of the 13th matting results and the 26th matting results. 1st column: the input images. 2nd column: the standard matting results. 3rd column: the matting result with the PSO. 4th column: the matting result with the D-EWA

In addition, It has been demonstrated that the total search performance of EWA is better than some popular and state-of-art metaheuristic algorithms, such as ABC [3], ACO [10], GA [6], DE [13]. Therefore, in experiments, these search algorithms are not used for comparison. The visual matting

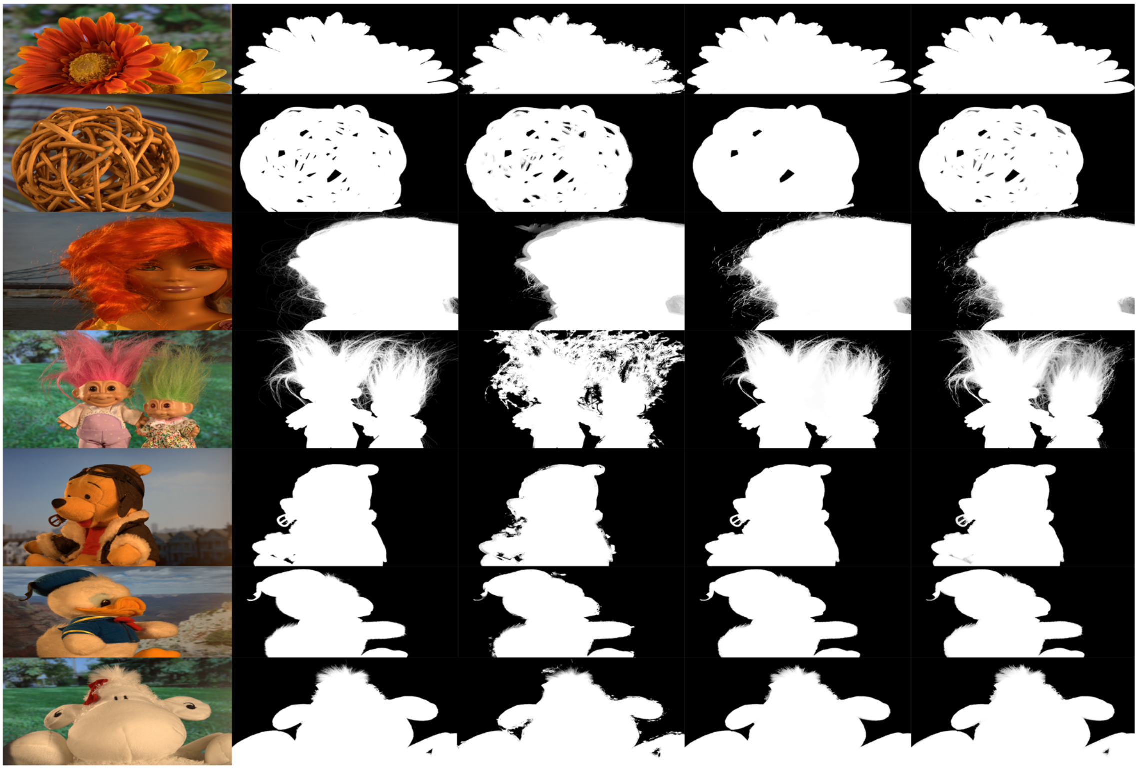

Fig. 8 Visual comparisons of matting results. 1st column: the input images. 2nd column: the standard matting results. 3rd column: the matting results with random search algorithm. 4th column: the matting results with PSO. 5th column: the matting results with the D-EWA

effects and the quantitative comparisons of the matting results are given below.

In experiments, a standard benchmark dataset [12] was used. This benchmark dataset includes twenty-seven groups of images. Every group of images has three images and they are the input image, the corresponding trimap, and the standard matting result. We use the sampling-based image matting method to implement matting for each input image and apply different search algorithms to search the best foreground–background sample pair in sample optimization step. The obtained matting results will compare with the corresponding standard matting results to test the quality of matting. At first, we compare the visual matting effects between the random search algorithm and the proposed D-EWA. These results are shown in Figs. 4 and 5. By observing, we can find that the total matting effects with the proposed D-EWA are closer to the standard matting effects. Then, we compare the visual matting effects between the particle swarm optimization and the proposed D-EWA in Figs. 6 and 7. We can find that the matting effects with the particle swarm optimization are closer to the matting effects with the D-EWA as a whole. However, in some of the details of the matting, the matting results with the D-EWA are closer to the standard matting results. These findings are understandable because the best foreground–background sample pairs of the undetermined pixels located in these regions are found by the D-EWA. The all visual matting effects are shown in Figs. 8, 9, 10 and 11. Intuitively, we can make a preliminary conclusion that the proposed discrete earthworm optimization algorithm (D-EWA) can achieve more efficient search performance in sample optimization step and obtain more accurate matting results (Fig. 11).

In order to further verify our above conclusion, the quantitative comparisons of the matting results are also conducted. In experiments, we use the mean square error (MSE) to accurately measure the gap between the matting result obtained in experiments and the standard matting results provided in [12]. The mean square error (MSE) is a classical measure, which is used in the study of the image matting for evaluating the quality of matting result. A smaller MSE indicates that the matting result obtained in experiments is closer to the standard matting results. The comparisons of the Mean Squared Error (MSE) among the random search algorithm, the particle swarm optimization and the discrete earthworm optimization algorithm are recorded in Table 1. By comparing the MSE values among the the random search algorithm, the particle swarm optimization and the discrete earthworm optimization algorithm, we can find that the MSE values of the proposed D-EWA are smaller than the values of the random search algorithm on all images. This finding is agree

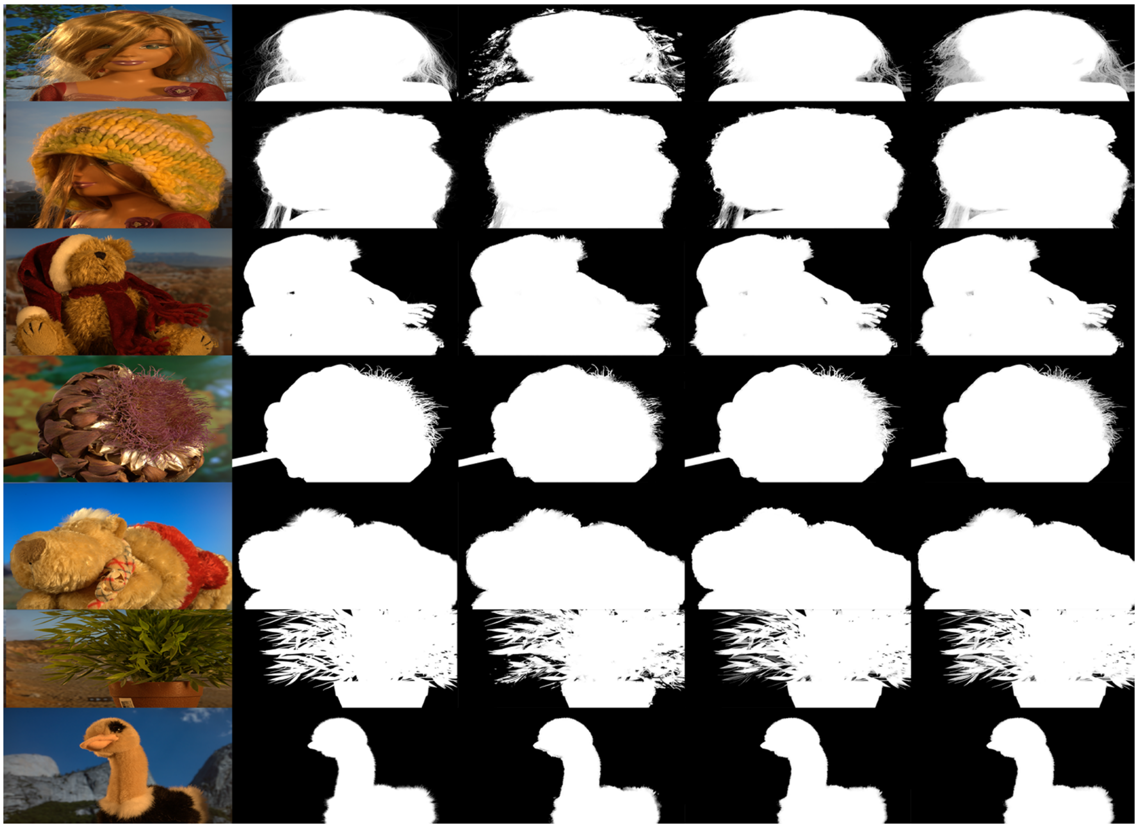

Fig. 9 Visual comparisons of matting results. 1st column: the input images. 2nd column: the standard matting results. 3rd column: the matting results with random search algorithm. 4th column: the matting results with PSO. 5th column: the matting results with the D-EWA

with an above conclusion that the qualities of the matting results with the proposed D-EWA are better than the qualities with the random search algorithm. By further comparing the MSE values between the particle swarm optimization and the proposed D-EWA, we find that the MSE values of the proposed D-EWA are also smaller than the values of the particle swarm optimization on twenty-two images, except for the 1st, 9th, 10th, 11th, 22th images. The total matting quality with the D-EWA is better than the matting quality with the particle swarm optimization. Therefore, these findings agree with our above conclusion that the proposed discrete earthworm optimization algorithm (D-EWA) can achieve more efficient search performance in sample optimization step and obtain more accurate matting results.

The random search algorithm [7] has been proved to be a feasible search algorithm to solve the sample optimization problem for sampling-based image matting. However, the robustness of this random search algorithm is not enough because of the property of random. By utilizing the bio-inspired search strategies and the information among the population, the metaheuristic algorithm, such as PSO, has been prove that it is a kind of promising search algorithm for solving the sample optimization problem [9]. In this study, considering the property of the sample optimization problem, we upgrade the earthworm optimization algorithm [15] to a discrete version. The experimental results show that the proposed discrete earthworm optimization algorithm (D-EWA) is a more efficient search algorithm and can obtain more accurate matting results.

5 Conclusion

The sample optimization problem in sampling-based image matting methods is a large-scale combinatorial optimization problem. In this paper, in order to improve the accuracy of matting for sampling-based image matting methods, we propose an efficient search algorithm to solve the sample optimization problem. The proposed algorithm is based on the earthworm optimization algorithm. In order to improve the search performance of the earthworm optimization algorithm, we upgrade two reproductions and the cauchy mutation in the earthworm optimization algorithm to discrete calculations. The experiments prove that the proposed discrete earthworm optimization algorithm can efficiently find the best foreground–background sample pairs and improve the accuracy of matting for sampling-based image matting methods.

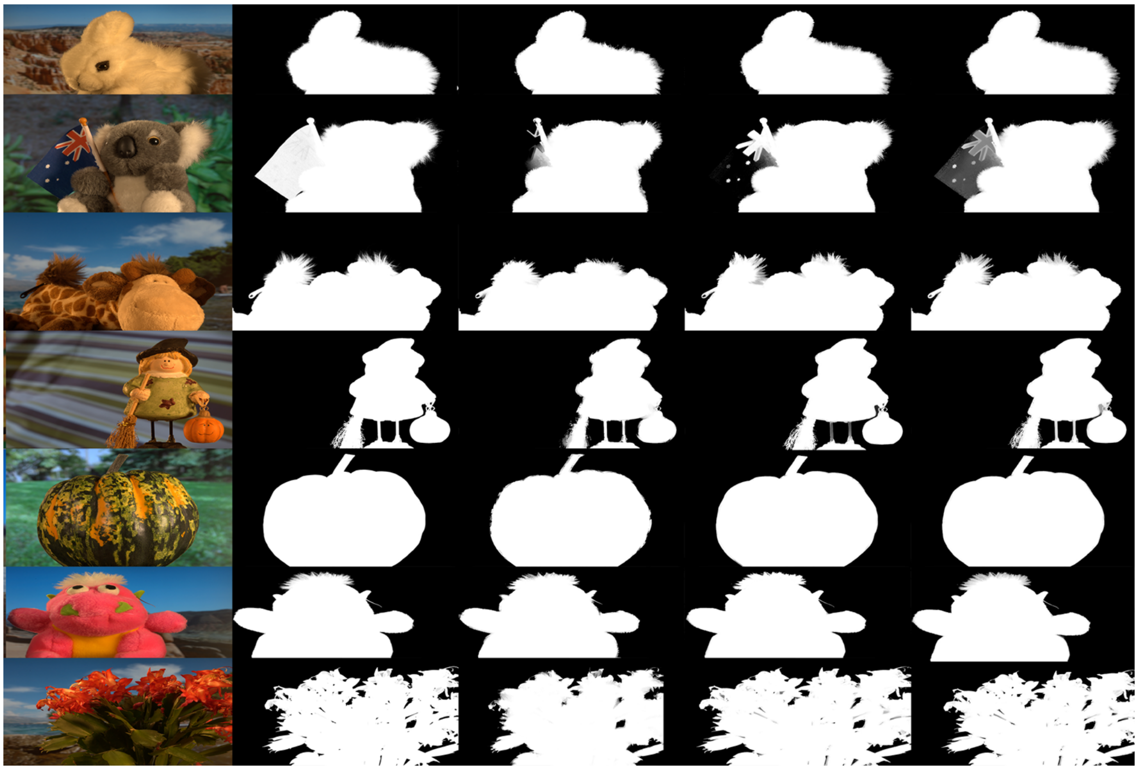

Fig. 10 Visual comparisons of matting results. 1st column: the input images. 2nd column: the standard matting results. 3rd column: the matting results with random search algorithm. 4th column: the matting results with PSO. 5th column: the matting results with the D-EWA

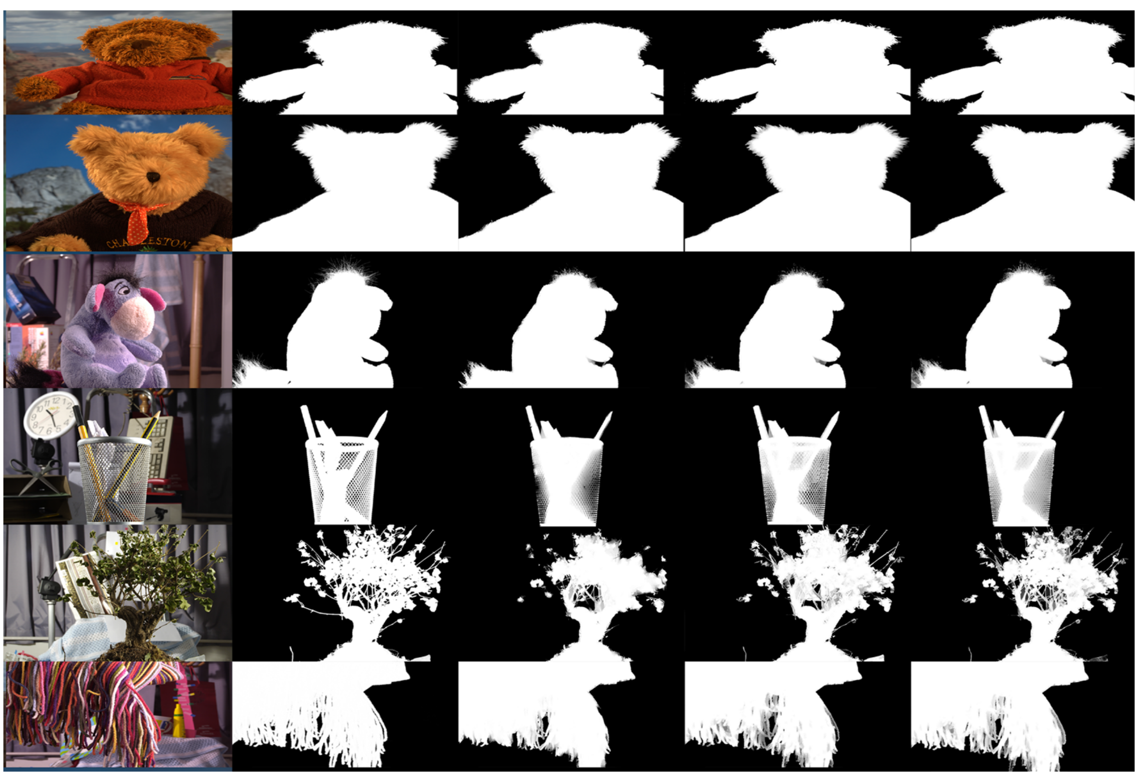

Fig. 11 Visual comparisons of matting results. 1st column: the input images. 2nd column: the standard matting results. 3rd column: the matting results with random search algorithm. 4th column: the matting results with PSO. 5th column: the matting results with the D-EWA

Table 1 Comparisons of the Mean Squared Error

No.	Random search algorithm	PSO algorithm	D-EWA algorithm
$Image\_01$	13.90×10^{-3}	1.25×10^{-3}	1.28×10^{-3}
$Image\_02$	7.02×10^{-3}	8.23×10^{-3}	1.63×10^{-3}
$Image\_03$	13.00×10^{-3}	4.21×10^{-3}	3.18×10^{-3}
$Image\_04$	100.17×10^{-3}	20.10×10^{-3}	6.18×10^{-3}
$Image\_05$	15.80×10^{-3}	2.20×10^{-3}	1.54×10^{-3}
$Image\_06$	10.22×10^{-3}	2.67×10^{-3}	2.10×10^{-3}
$Image\_07$	15.65×10^{-3}	2.57×10^{-3}	0.95×10^{-3}
$Image\_08$	57.26×10^{-3}	12.32×10^{-3}	7.08×10^{-3}
$Image\_09$	12.54×10^{-3}	2.50×10^{-3}	2.74×10^{-3}
$Image\_10$	8.12×10^{-3}	3.11×10^{-3}	3.17×10^{-3}
$Image\_11$	12.97×10^{-3}	4.04×10^{-3}	4.20×10^{-3}
$Image\_12$	4.86×10^{-3}	2.82×10^{-3}	1.18×10^{-3}
$Image\_13$	57.17×10^{-3}	21.58×10^{-3}	8.38×10^{-3}
$Image\_14$	4.60×10^{-3}	2.00×10^{-3}	1.33×10^{-3}
$Image\_15$	9.25×10^{-3}	3.88×10^{-3}	3.47×10^{-3}
$Image\_16$	80.49×10^{-3}	62.30×10^{-3}	49.94×10^{-3}
$Image\_17$	10.92×10^{-3}	2.58×10^{-3}	1.95×10^{-3}
$Image\_18$	11.64×10^{-3}	3.81×10^{-3}	2.41×10^{-3}
$Image\_19$	6.18×10^{-3}	0.94×10^{-3}	0.80×10^{-3}
$Image\_20$	4.45×10^{-3}	1.94×10^{-3}	1.51×10^{-3}
$Image\_21$	22.50×10^{-3}	4.84×10^{-3}	3.92×10^{-3}
$Image\_22$	11.15×10^{-3}	1.94×10^{-3}	2.15×10^{-3}
$Image\_23$	4.49×10^{-3}	3.76×10^{-3}	1.30×10^{-3}
$Image\_24$	6.29×10^{-3}	4.45×10^{-3}	3.75×10^{-3}
$Image\_25$	24.96×10^{-3}	15.50×10^{-3}	13.43×10^{-3}
$Image\_26$	47.48×10^{-3}	25.44×10^{-3}	18.82×10^{-3}
$Image\_27$	20.88×10^{-3}	16.33×10^{-3}	10.38×10^{-3}

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Compliance with ethical standards

Conflict of interest All Authors of this paper declare that we have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

1. Beyer W (1964) Traveling matte photography and the blue screen system. American Cinematographer, New York
2. Chen Q, Li D, Tang CK (2013) Knn matting. IEEE Trans Pattern Anal Mach Intell 35(9):2175–2188
3. Dervis K, Bahriye B (2007) A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. J Global Optim 39(3):459–471
4. Eberhart R, Kennedy J (1995) A new optimizer using particle swarm theory. In: Proceedings of the sixth international symposium on micro machine and human science, pp. 39–43
5. Gastal ESL, Oliveira MM (2010) Shared sampling for real-time alpha matting. Comput Graph Forum 29(2):575–584
6. Goldberg DE (1998) Genetic algorithms in search, optimization, and machine learning. Addison-Wesley Pub Co, Boston
7. He K, Rhemann C, Rother C, Tang X, Sun J (2011) A global sampling method for alpha matting. In: IEEE conference on computer vision and pattern recognition (CVPR), pp. 2049–2056
8. Levin A, Lischinski D, Weiss Y (2008) A closed-form solution to natural image matting. IEEE Trans Pattern Anal Mach Intell 30(2):228–242
9. Lv L, Huang H, Cai Z, Hu H (2015) Using particle swarm large-scale optimization to improve sampling-based image matting. In:

The companion publication of the 2015 annual conference on genetic and evolutionary computation, pp. 957 – 961
10. Marco D, Vittorio M, Alberto C (1996) The ant system: optimization by a colony of cooperating agents. IEEE Trans Syst Man Cybern Part B Cybern 26(1):29–41
11. Rhemann C, Rother C, Gelautz M (2008) Improving color modeling for alpha matting. In: Proceedings of the British machine vision conference (BMVC) 2008, pp 1155–1164
12. Rhemann C, Rother C, Wang J, Gelautz M, Kohli P, Rott P (2009) A perceptually motivated online benchmark for image matting. In: IEEE conference on computer vision and pattern recognition (CVPR), pp 1826–1833
13. Storn R, Price K (1997) Differential evolution: a simple and efficient heuristic for global optimization over continuous spaces. Global Optim 11(4):341–359
14. Sun J, Jia J, Tang CK, Shum HY (2004) Poisson matting. ACM Trans Graph 23(3):315–321
15. Wang GG, Deb S, dos Santos Coelho L (2015) Earthworm optimization algorithm: a bio-inspired metaheuristic algorithm for global optimization problems. Int J Bio-Inspired Comput 200x:X
16. Wang J, Cohen MF (2007) Optimized color sampling for robust matting. In: IEEE computer society conference on computer vision and pattern recognition (CVPR), pp 1–8
17. Wikipedia: Matte (filmmaking). [Online]. http://en.wikipedia.org/wiki/Matte_(filmmaking) (1980)
18. Zhu Q, Shao L, Li X, Wang L (2015) Targeting accurate object extraction from an image: a comprehensive study of natural image matting. IEEE Trans Neural Netw Learn Syst 26(2):185–207