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Artificial bee colony (ABC) optimized edge potential function (EPF) approach to target recognition for low-altitude aircraft

Chunfan Xu *, Haibin Duan

School of Automation Science and Electrical Engineering, Beijing University of Aeronautics and Astronautics, Beijing 100191, PR China

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ABSTRACT

This paper describes a novel shape-matching approach to visual target recognition for aircraft at low altitude. An artificial bee colony (ABC) algorithm with edge potential function (EPF) is proposed to accomplish the target recognition task for aircraft. EPF is adopted to provide a type of attractive pattern for a matching contour, which can be exploited by ABC algorithm conveniently. In this way, the best match can be obtained when the sketch image translates, reorients and scales itself to maximize the potential value. In addition, the convergence proof and computational complexity for the ABC algorithm are also given in detail. Series of experimental results demonstrate the feasibility and effectiveness of our proposed approach over the traditional genetic algorithm (GA). The proposed method can also be applied to solve the target recognition problems in mobile robots, industry production lines, and transportations.

1. Introduction

Target recognition is a key issue to achieve autonomous reconnaissance and attack for aircraft at low altitude. In many countries, target recognition technology for aircrafts at low altitude is highly confidential, and it is accordingly difficult to see its specific technical details (Shi et al., 2006). In order to obtain accurate identification results and hence to meet the practical requirements of aircrafts reconnaissance system, the proposed target recognition method must be efficient, stable, and convenient for promotion (Zhou et al., 2009; Francisco et al., 2009). Among all the methods, shape representation and matching is a very important aspect, and has been extensively used for solving object recognition problem (Scasellati and Alexopoulos, 1994; Belongie et al., 2002).

Generally, shape matching schemes involve two general steps: feature extraction, and similarity measuring (Veltkamp, 2001). Various methods have been used to determine the similarity between planar shapes, including moment-based matching (Hu, 1962; Taubin and Copper, 1991), Hausdorff distance based matching (Saber and Tekalp, 1997; Huttenlocker et al., 1993), and so on. Edge Potential Function (EPF) is a newly-developed similarity evaluating measure, which was firstly proposed by Minh-Son et al. (2007). This conception is derived from the potential generated by charged particles and has been proved its feasibility and reliability over Hausdorff distance and Chamfer distance measures.

Artificial bee colony (ABC) algorithm is a new optimization method, which is based on swarm intelligence and motivated by the intelligent behavior of honey bees. ABC algorithm has been proved to possess a better performance in function optimization problem, compared with genetic algorithm (GA), differential evolution (DE) and particle swarm optimization (PSO) (Karaboga and Basturk, 2007; Karaboga and Basturk, 2008). The main advantage of ABC algorithm lies in that it conducts local search in each iteration, thus the probability of finding the optimal results is significantly increased, which can efficiently avoid local optimum to a larger extent.

In this work, the EPF is adopted to provide a type of attractive pattern for a matching contour, which is conveniently exploited by ABC algorithm. In this way, the best match can be obtained when the sketch image translates, reorients and scales itself to maximize the potential value. The convergence for ABC algorithm is also proved theoretically.

The remainder of this paper is organized as follows. Section 2 introduces the principle of EPF. Section 3 describes the basic principle and implementation procedure of ABC algorithm in detail, and the convergence proof of the ABC algorithm is also presented in this section. Section 4 proposes our ABC optimized EPF approach to target recognition task. Then, in Section 5, series of comparison experiments are conducted to verify the feasibility and effectiveness of our proposed approach over the traditional genetic algorithm. Our concluding remarks and future work are contained in the final section.

2. The principle of EPF

EPF was firstly put forward by Minh-Son et al. (2007). This conception was derived from the potential generated by charged

* Corresponding author. Fax: +86 10 82338672.
E-mail address: xiaofang88s@hotmail.com (C. Xu).

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particles, and was especially adopted to model the attraction generated by edge structures contained in an image over similar curves.

A set of point charges Q_i in a homogeneous background can generate a potential, the intensity of which depends on the distance from the charges and the electrical permittivity of the medium ε, namely

$$v(\vec{r}) = \frac{1}{4\pi\varepsilon}\sum_i \frac{Q_i}{|\vec{r}-\vec{r}_i|} \tag{1}$$

where $\vec{r}$ and $\vec{r}_i$ are the observation point and charge locations, respectively. And the exact potential for a position in electric field amounts to the sum of potentials generated by each charged point.

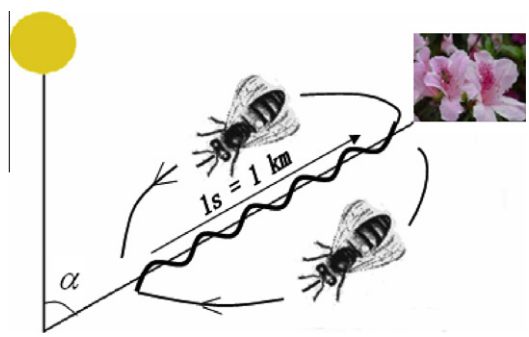


Fig. 1. Waggle dance of honey bees.

In complete analogy with the above behavior, in our model, (x, y) represents the coordinates of any point of an image, and the ith edge point in the image at coordinates (x_i, y_i) can be assumed to be equivalent to a point charged $Q_{eq}(x_i, y_i)$, contributing to the potential of any image pixel (x, y)

$$EPF(x,y) = \frac{1}{4\pi\varepsilon_{eq}}\sum_i \frac{Q_{eq}(x_i,y_i)}{\sqrt{(x-x_i)^2+(y-y_i)^2}} \tag{2}$$

Minh-Son Dao also outlined several EPF models (Minh-Son et al., 2007), among which we adopt the Windowed EPF (WEPF) model in order to simplify the calculations, as well as improving the robustness of shape-matching in cluttered environments. WEPF defines a window W beyond which edge points are ignored, which can be expressed as follows:

$$EPF(x,y) = \frac{Q}{4\pi\varepsilon_{eq}}\sum_{(x_i,y_i)\in W} \frac{1}{\sqrt{(x-x_i)^2+(y-y_i)^2}} \tag{3}$$

where ε_{eq} is a constant related with the image background situation, and Q is equal to the charge of each edge point $Q_{eq}(x_i, y_i)$. Then the edge potential of any pixel of an image can be obtained from an edge map, which is extracted from the image. The edge potential represents a type of attraction field in analogy with the field generated by a charged element.

To complete the model, the searched target template to be matched can be considered as a test object, which is expected to be attracted by a set of equivalent charged points. In this way, the higher the similarity between the searched object and visual objects in the image, the higher the total attraction engendered by the edge field. As a result, EPF can be particularly used

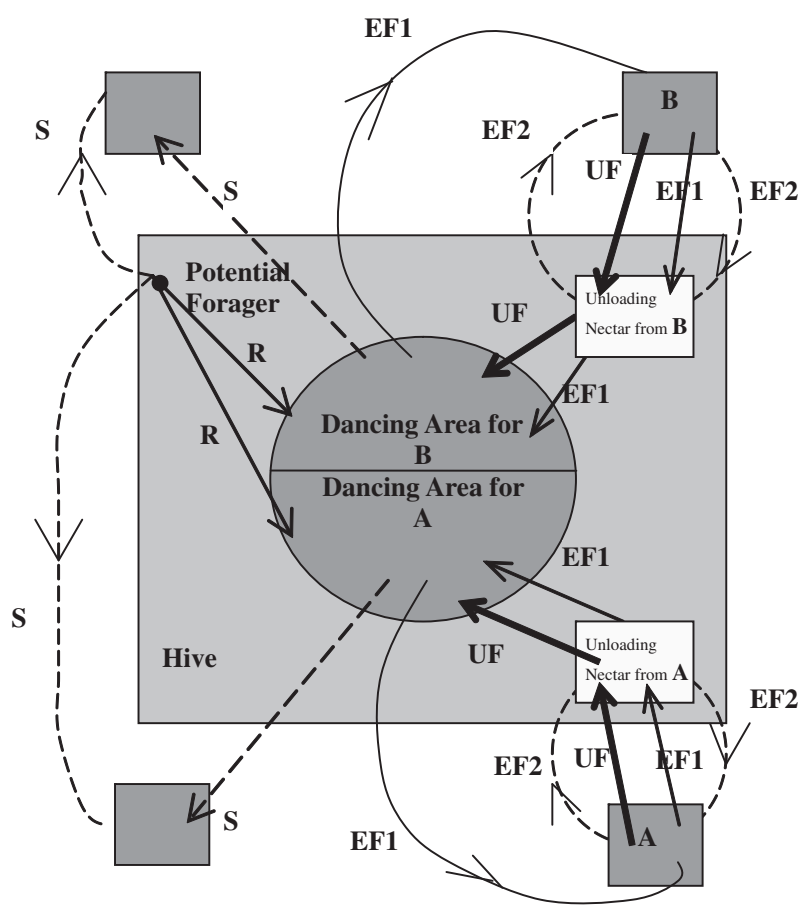


Fig. 2. The behavior of honey bee foraging for nectar.

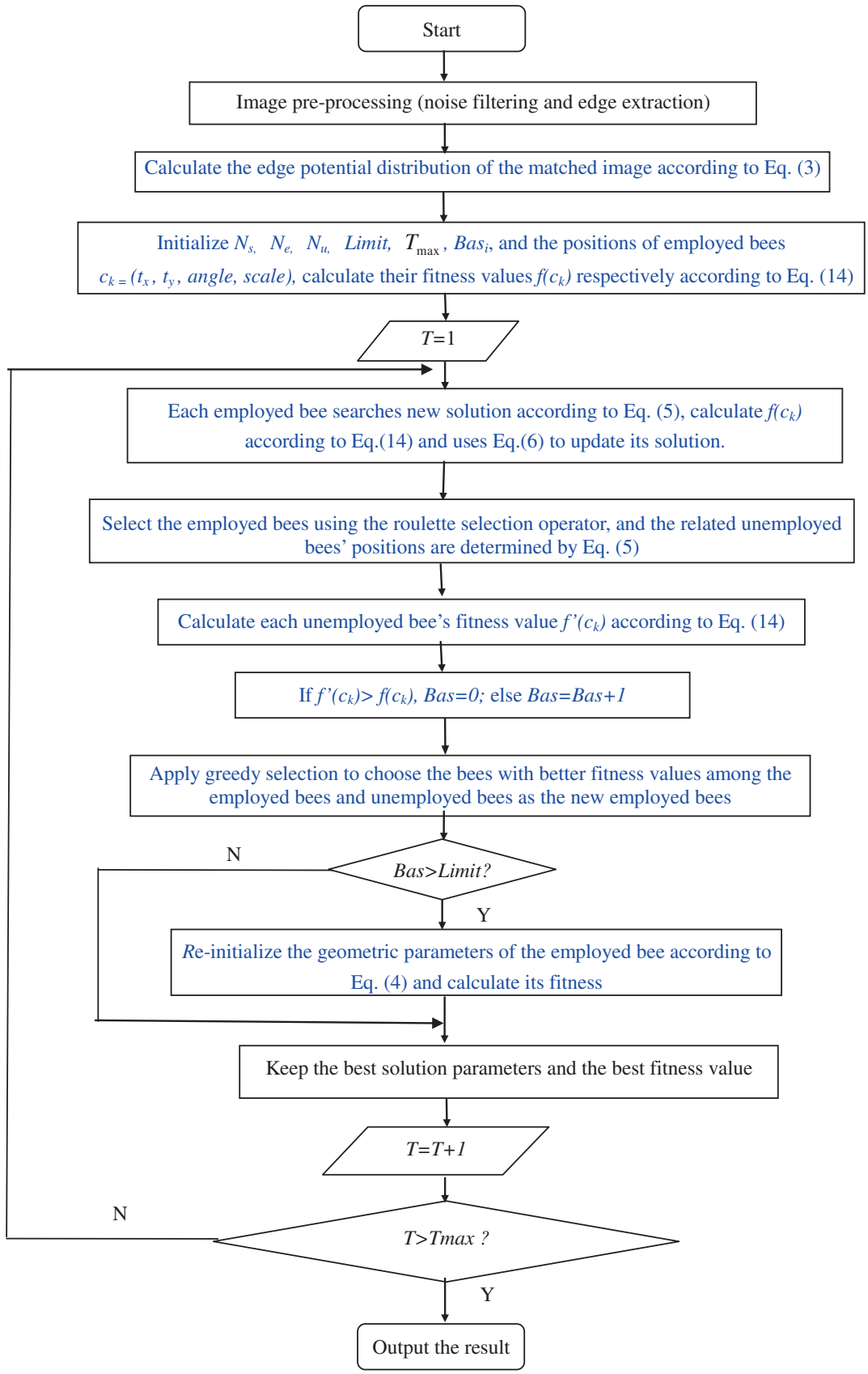


Fig. 3. The procedure of our proposed method.

as the similarity measure for shape matching problem, for it implicitly includes some important features such as edge position, strength, and continuity, in a unique powerful representation of the edge.

3. ABC algorithm

ABC algorithm was firstly proposed by simulating the self-organization simulation model of honey bees (Seeley, 1995). In this model, although each bee only performs one single task, yet through a variety of information communication ways between bees, the entire colony can complete a number of complex works such as hives building, pollen harvest and so on. Then in 2003, Dušan Teodorović further introduced a bee colony optimization (BCO) algorithm (Teodorovic and Orco, 2005). Then, Dervis Karaboga put forward an improved ABC algorithm (Karaboga and Basturk, 2007).

3.1. Basic principles of the ABC algorithm

Karlvon Frisch, a famous Nobel Prize winner, once found that in nature, although each bee only performs one single task, yet through a variety of information communication ways between

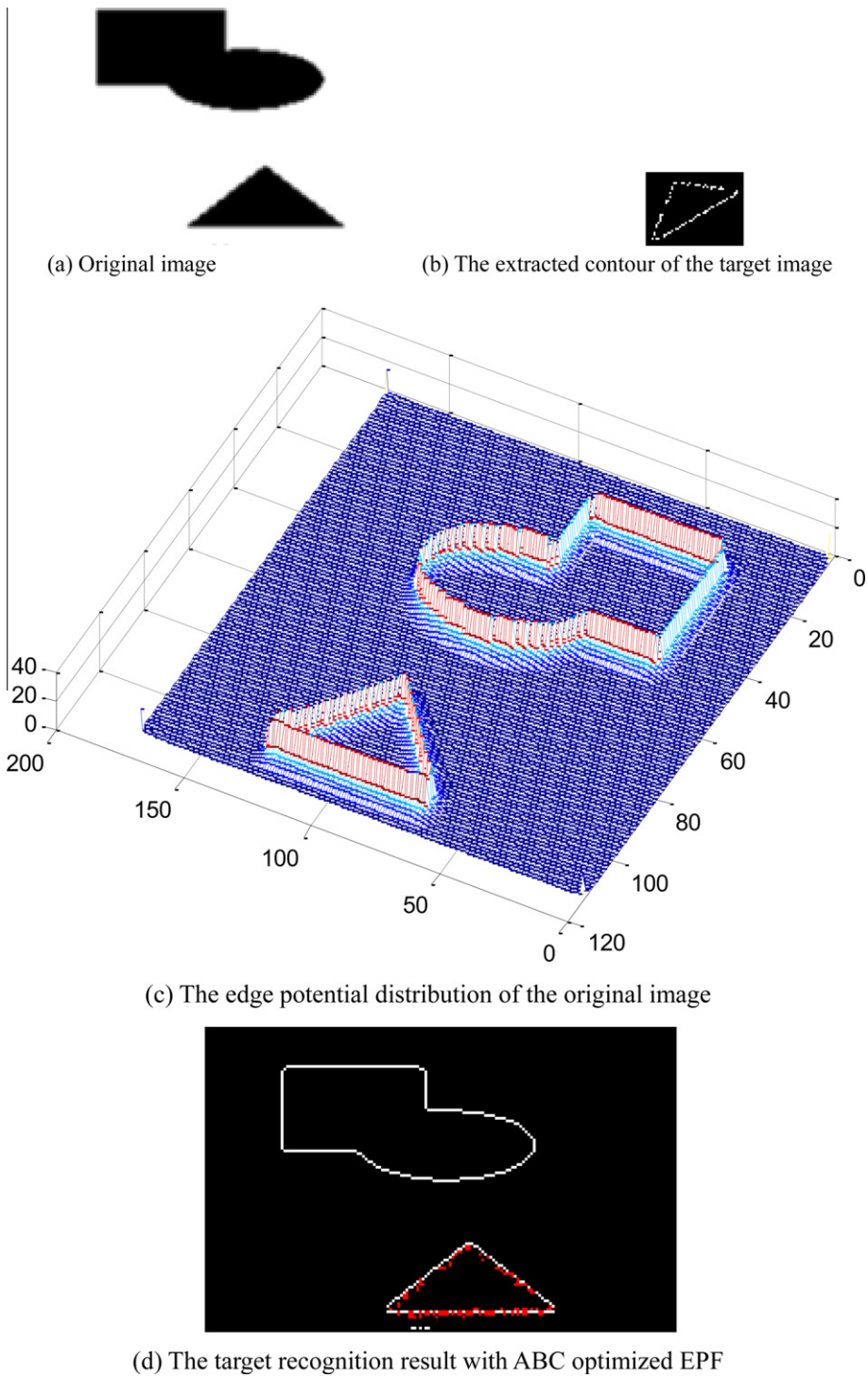
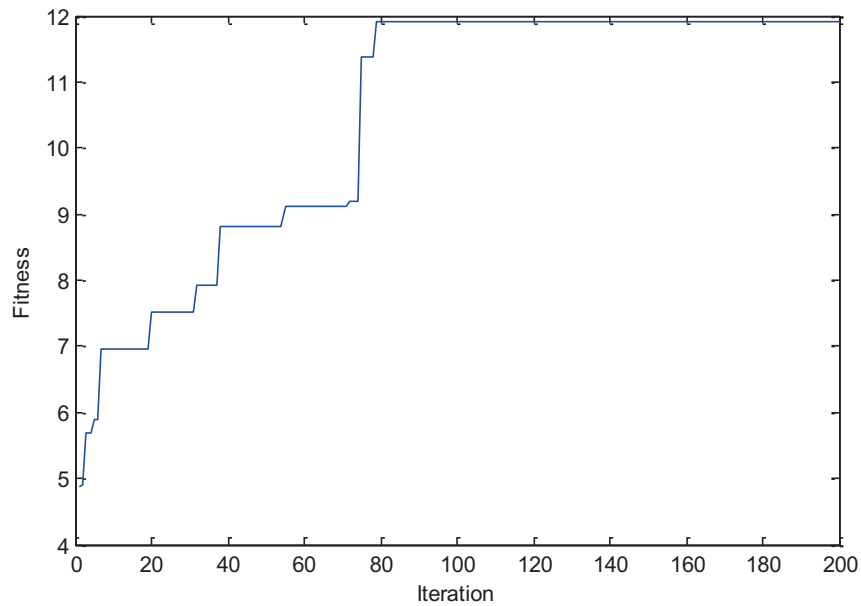


Fig. 4. Experimental results of Case 1 by using our proposed method. (a) Original image, (b) the extracted contour of the target image, (c) the edge potential distribution of the original image, (d) the target recognition result with ABC optimized EPF and (e) the evolution curve of ABC algorithm.



(e) The evolution curve of ABC algorithm

Fig. 4 (*continued*)

bees such as waggle dance and special odor, the entire colony can always easily find food resources that produce relatively large amounts of nectar, hence realize its self-organizing behavior (Fathian et al., 2007). In nature, the bees crawl along a straight line, and then turn left, moving as figure eight and swinging their belly. Such a dance is called waggle dance, and the angle between the gravity direction and the centre axis of the dance is exactly equal to the angle between the sun and food source (as shown in Fig. 1) (Fathian et al., 2007).

In addition, waggle dance of the bees can also deliver more detailed information about the food sources such as distance and direction. Then each bee in the hive selects a food source to search for nectar, or researches new food sources around the bee hive, according to the information delivered by the other bee's waggle dance (Singh, 2009). Through this kind of information exchanging and learning, the whole colony would always find relatively prominent nectar source.

In order to introduce the model of forage selection that leads to the emergence of collective intelligence of honey bee swarms. We need to define three essential components: food sources, unemployed foragers and employed foragers (Jeanne, 1986).

(1) *Food sources* (A and B in Fig. 2): For the sake of simplicity, the "profitability" of a food source can be represented with a single quantity (Singh, 2009), which corresponds to the similarity value in our target recognition problem.
(2) *Unemployed foragers* (UF in Fig. 2): Unemployed foragers are continually looking out for a food source to exploit. There are two types of unemployed foragers: scouts (S in Fig. 2) and onlookers (R in Fig. 2).
(3) *Employed foragers* (EF1 and EF2 in Fig. 2): They carry with them information about this particular source, the profitability of the source and share this information with a certain probability.

After the employed foraging bee loads a portion of nectar from the food source, it returns to the hive, unloads the nectar to the food area in the hive, and converts into any kind of bees (UF or EF) in accordance with the profit of the searched food sources.

3.2. Mathematical description of ABC algorithm

Define N_s as the total number of bees, N_e as the colony size of the employed bees and N_u as the size of unemployed bees, which satisfy the equation $N_s = N_e + N_u$. We usually set N_e equal to N_u. D is the dimension of individual solution vector, $S = R^D$ represents individual search space, and S^{N_e} denotes the colony space of employed bees. An employed bee colony can be expressed by N_e dimension vector $\vec{X} = (X_1, \ldots, X_{N_e})$, where $X_i \in S$ and $i \leqslant N_e$. $\vec{X}(0)$ means the initial employed bee colony, while $\vec{X}(n)$ represents employed bee colony in the nth iteration. Denote $f : S \to R^+$ as the fitness function, and the standard ABC algorithm can be expressed as follows:

Step 1 Randomly initialize a set of feasible solutions $(X_1, \ldots, X_{N_s})$, and the specific solution X_i can be generated by

$$X_i^j = X_{\min}^j + rand(0,1)(X_{\max}^j - X_{\min}^j) \tag{4}$$

where $j \in \{1, 2, \ldots, D\}$ is the jth dimension of the solution vector. Calculate the fitness value of each solution vector respectively, and set the top N_e best solutions as the initial population of the employed bees $\vec{X}(0)$.

Step 2 For an employed bee in the nth iteration $X_i(n)$, search new solutions in the neighborhood of the current position vector according to the following equation

$$V_i^j = X_i^j + \varphi_i^j\left(X_i^j - X_k^j\right) \tag{5}$$

where $V \in S$, $j \in \{1, 2, \ldots, D\}$, $k \in \{1, 2, \ldots, N_e\}$, $k \neq i$, k and j are randomly generated. φ_i^j is a random number between -1 and 1.Generally, this searching process is actually a random mapping from individual space to individual space, and this process can be denoted with $T_m : S \to S$, and its probability distribution is clearly only related to current position vector $X_i(n)$, and has no relation with past location vectors as well as the iteration number n.

Step 3 Apply the greedy selection operator $T_s : S^2 \to S$ to choose the better solution between searched new vector V_i and the original vector X_i into the next generation. Its probability distribution can be described as follows:

$$P\{T_s(X_i, V_i) = V_i\} = \begin{cases} 1, f(V_i) \geqslant f(X_i) \\ 0, f(V_i) < f(X_i) \end{cases} \tag{6}$$

The greedy selection operator ensures that the population is able to retain the elite individual, and accordingly the evolution will not retreat. Obviously, the distribution of T_s is has no relation with the iteration n.

Step 4 Each unemployed bee selects an employed bee from the colony according to their fitness values. The probability distribution of the selection operator $T_{s1} : S^{N_e} \to S$ can described as follows.

$$P\{T_{s1}(\vec{X}) = X_i\} = \frac{f(X_i)}{\sum_{m=1}^{N_e} f(X_m)} \tag{7}$$

Step 5 The unemployed bee searches in the neighborhood of the selected employed bee's position to find new solutions (see Eq. (5)). The updated best fitness value can be denoted with *f_best*, and the best solution parameters can be expressed with $(x_1, x_2, \ldots, x_D)$.

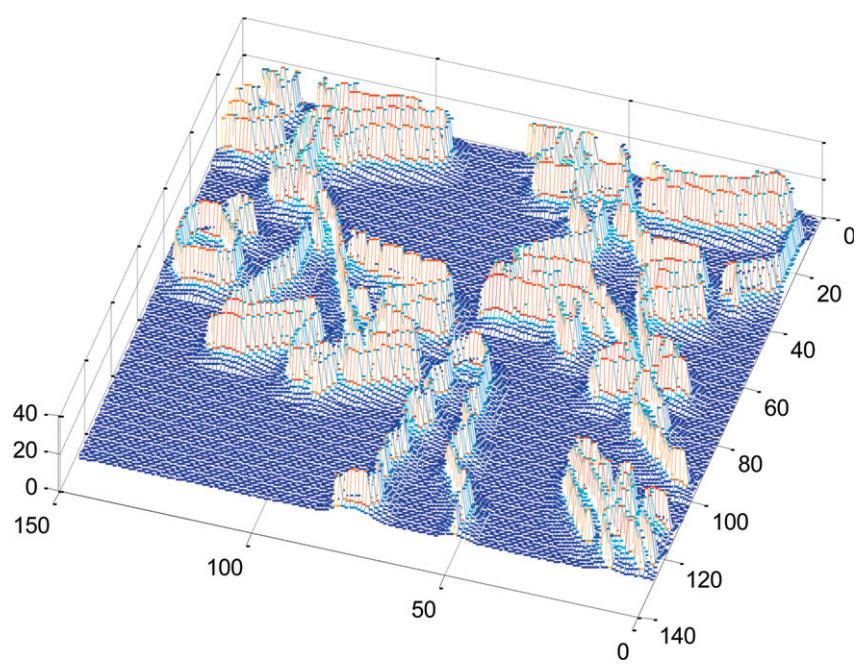
Step 6 If the searching times surrounding an employed bee *Bas* exceeds a certain threshold *Limit*, but still could not find better solutions, then the location vector can be re-initialized randomly according to the following equation.

$$X_i(n+1) = \begin{cases} X_{\min} + rand(0,1)(X_{\max} - X_{\min}), & Bas_i \geqslant Limit \\ X_i(n), & Bas_i < Limit \end{cases} \tag{8}$$

Step 7 If the iteration value is larger than the maximum number of the iteration (that is, $T > T_{\max}$), output the optimal fitness value *f_best* and correlative parameters $(x_1, x_2, \ldots, x_D)$. If not, go to Step 2.

(a) Original image

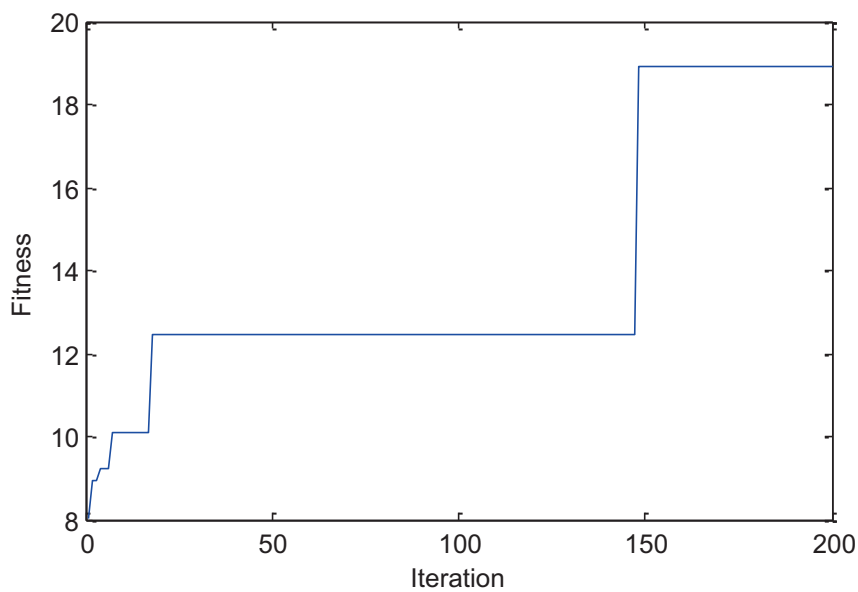
(b) The extracted edge of the identify target



(c) The edge potential distribution of the orginal image

Fig. 5. The results of Case 2 by using our proposed method. (a) Original image, (b) the extracted edge of the identify target, (c) the edge potential distribution of the original image, (d) the target recognition results with ABC optimized EPF and (e) the evolution curve of the ABC algorithm.

(d) The target recognition results with ABC optimized EPF



(e) The evolution curve of the ABC algorithm

Fig. 5 (*continued*)

Step 6 is a most prominent aspect making ABC algorithm different from other algorithms, which is designed to enhance the diversity of the population to prevent the population from trapping into the local optimum. Obviously, this step can improve the probability of finding the best solution efficiently, and make the ABC algorithm perform much better.

3.3. Convergence and complexity analysis of the ABC algorithm

Without considering the impact of the above Step 6, note

$$T = T_m \circ T_s \circ T_{s1} \circ T_m \circ T_s \tag{9}$$

Then the ABC algorithm can be expressed as:

$$\vec{X}(n+1) = T(\vec{X}(n)) = T_m \circ T_s \circ T_{s1} \circ T_m \circ T_s(\vec{X}(n)) \tag{10}$$

Definition 1. The global optimal solution sets can be described as $M = \{X; \forall Y \in S, s.t. f(X) \geqslant f(Y)\}$.

Definition 2. For any initial position distributions of employed bees $\vec{X}(0) = S_0 \in S$, $\lim_{n\to\infty} P\{\vec{X}(n) \in M | \vec{X}(0) = S_0\} = 1$ means that the algorithm strongly converges to the global optimal solution sets in probability, while $\lim_{n\to\infty} P\{\vec{X}(n) \cap M \neq \emptyset | \vec{X}(0) = S_0\} = 1$ indicates a weak convergence to the global optimal solution sets (Zhang and Liang, 2003).

Lemma 1. *The evolution direction of the colony of ABC algorithm is unchangeable, i.e.* $f(X_i(n+1)) \geqslant f(X_i(n))$.

Proof. According to the greedy selection operator in Eq. (6), it is obvious that the ABC algorithm tends to retain individuals that have higher fitness values into the next generation, and as a result, the best fitness value of the colony can monotonically increase with generations. □

Lemma 2. *The population sequence of the ABC algorithm* $\{X(n), n \in N^+\}$ *is a finite Markov chain.*

Proof. As the solution space S of the colony is D-dimensional, which has a defined upper bound, a lower bound, a determined precision of the parameters, and the size of the bee colony N_e , thus, the state space for the employed bee colony S^{N_e} is finite.

From the formula (10) $\vec{X}(n+1) = T(\vec{X}(n)) = T_m \circ T_s \circ T_{s1} \circ T_m \circ T_s(\vec{X}(n))$, and the above algorithm description, we can obtain an obvious conclusion that T_m, T_s, T_{s1} has nothing to do with current generation n, and as a result, $X(n+1)$ is merely relevant with $X(n)$, which means that $\{X(n), n \in N^+\}$ is a finite homogeneous Markov chain. The transition probability of the colony is described as,

$$P\{X,Y\} = P\{X(n+1) = Y|X(n) = X\} = \begin{cases} \Pi_{k=1}^{N_e} P\{T(X(n))_k = Y_k\}, & \exists i_0 \in [1, N_e] \; s.t. f(Y_{i_0}) = \min f(X) \\ 0, & else \end{cases} \quad \square \tag{11}$$

Theorem 1. *The Markov chain of the ABC algorithm converges to the global optimal solution sets M in probability 1, i.e.*

$$\lim_{n\to\infty} P\{\vec{X}(n) \in M\} = 1$$

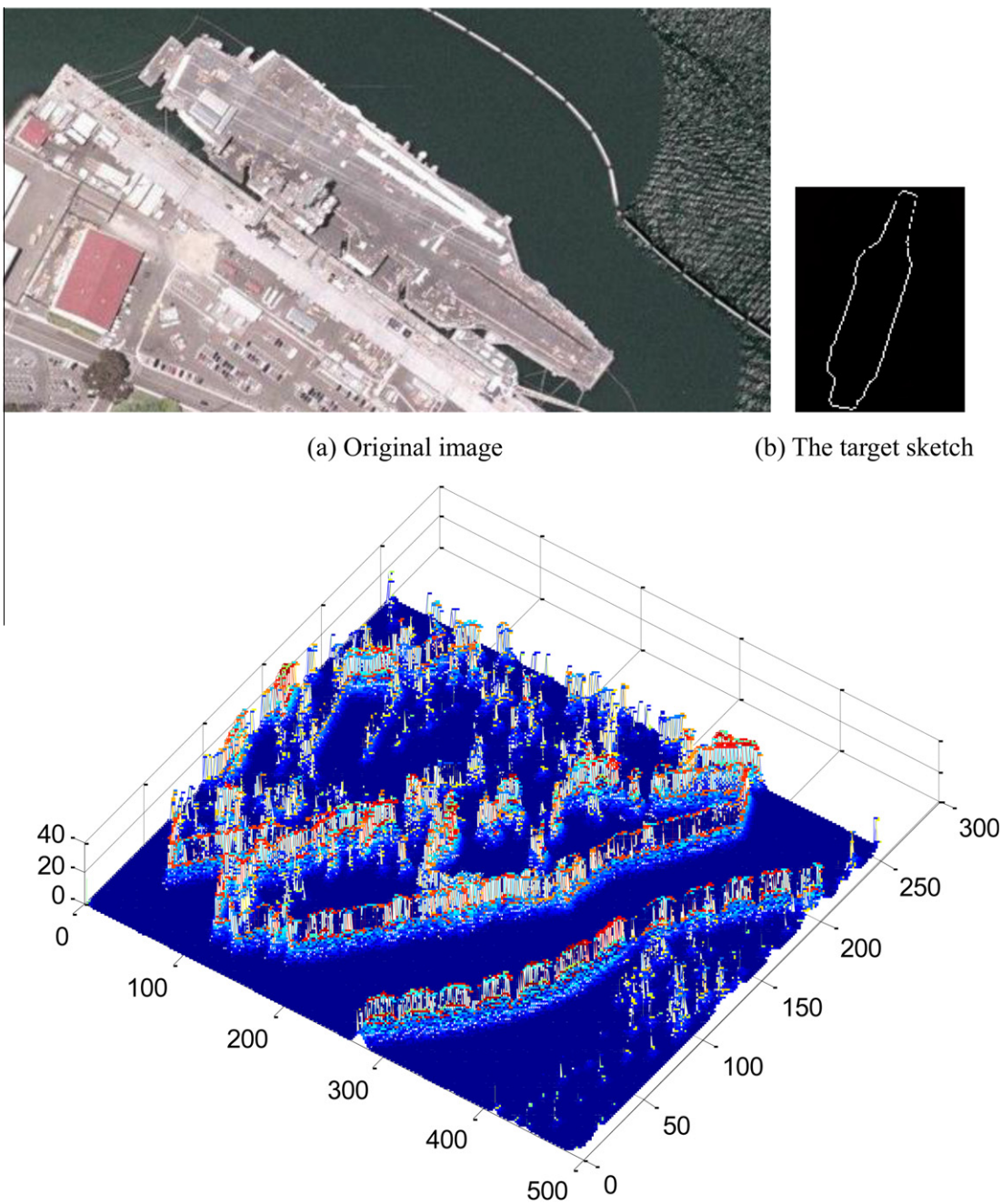
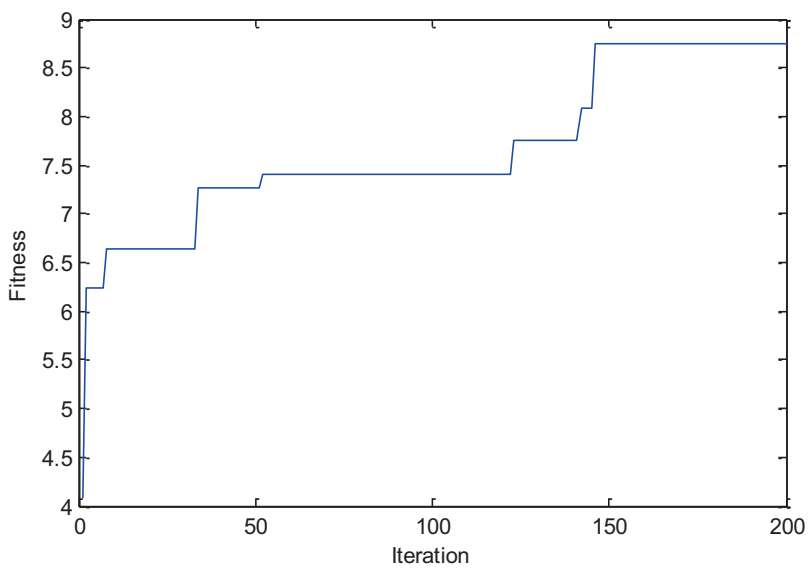


Fig. 6. Experimental results of Case 3 by using our proposed ABC optimized EPF method. (a) Original image, (b) the target sketch, (c) the edge potential distribution of the original image, (d) the results of target recognition and (e) The evolution curve of the ABC algorithm.

(d) The results of target recognition



(e) The evolution curve of the ABC algorithm

Fig. 6 (*continued*)

Proof. From Lemma 1, it is obvious that if $\vec{X}(n)$ has already entered the global optimal solution sets M, $\vec{X}(n+1)$ is bound to be concluded in M

$$P\{\vec{X}(n+1) \in M | \vec{X}(n) \in M\} = 1 \tag{12}$$

Then

$$\begin{aligned} P\{\vec{X}(n+1) \in M\} &= [1 - P\{\vec{X}(n) \in M\}] \cdot P\{\vec{X}(n+1) \in M | \vec{X}(n) \notin M\} \\ &\quad + P\{\vec{X}(n) \in M\} \cdot P\{\vec{X}(n+1) \in M | \vec{X}(n) \in M\} \\ &= [1 - P\{\vec{X}(n) \in M\}] \cdot P\{\vec{X}(n+1) \in M | \vec{X}(n) \notin M\} \\ &\quad + P\{\vec{X}(n) \in M\} \end{aligned}$$

Suppose

$$P\{\vec{X}(n+1) \in M | \vec{X}(n) \notin M\} \geqslant d(n) \geqslant 0$$

Then

$$\lim_{n\to\infty} \Pi_{i=1}^{n} [1 - d(i)] = 0$$

Thus

$$\begin{aligned} 1 - P\{\vec{X}(n+1) \in M\} &\leqslant [1 - d(n)][1 - P\{\vec{X}(n) \in M\}] \\ &\Rightarrow 1 - P\{\vec{X}(n+1) \in M\} \leqslant [1 - P\{\vec{X}(0) \\ &\in M\}] \cdot \Pi_{i=1}^{n} [1 - d(i)] \Rightarrow \lim_{n\to\infty} P\{\vec{X}(n+1) \in M\} \\ &\geqslant 1 - [1 - P\{\vec{X}(0) \in M\}] \cdot \lim_{n\to\infty} \Pi_{i=1}^{n} [1 - d(i)] \\ &\Rightarrow \lim_{n\to\infty} P\{\vec{X}(n+1) \in M\} \geqslant 1 \end{aligned}$$

However, $P\{\vec{X}(n+1) \in M\} \leqslant 1$, and as a result, according to the two restrictions mentioned above, we can easily get the conclusion that $\lim_{n\to\infty} P\{\vec{X}(n+1) \in M\} = 1$, which is equal to that $\lim_{n\to\infty} P\{\vec{X}(n) \in M\} = 1$.

It is obvious that the ABC algorithm excluding Step 6 can converge to the global optimal solution sets M in probability 1. If taking Step 6 into consideration, the algorithm's ability to jump out of local optimum can be increased, and accordingly, the algorithm can search the best solutions when the generation n is large enough, that is $\lim_{n\to\infty} P\{\vec{X}(n) \cap M \neq \emptyset\} = 1$. Therefore, the ABC algorithm is weakly converged to the global optimal solution sets M.

From the mathematical description of the ABC algorithm, it is clear that the computational complexity of the algorithm is $O\left(D^2 T_c N_s\right)$, where D represents the dimension of the problem to be solved, T_c denotes the iterations required to obtain the optimized solution, and N_s is the number of the bee population. The ABC algorithm can get the optimized solution with the desired computational cost. □

4. ABC optimized EPF approach to target identify

The implementation procedure of our proposed ABC optimized EPF approach to target recognition for aircraft at low altitude can be described as follows:

Step 1 *Image pre-processing*

(1) Obtain the image, and convert it into grayscale format for further edge detection operation.

(2) Filter the target image to remove the noise.Conduct filtering operation to the obtained grayscale image in order to mitigate the effect of noise. For this purpose, we applied the median filtering method, which was certified to have a especially good inhibiting effect towards pepper noise and Gaussian noise.

(3) Adopt canny edge extractor to detect the edges of the given image for the sake of obtaining proper binary distribution of the original image.

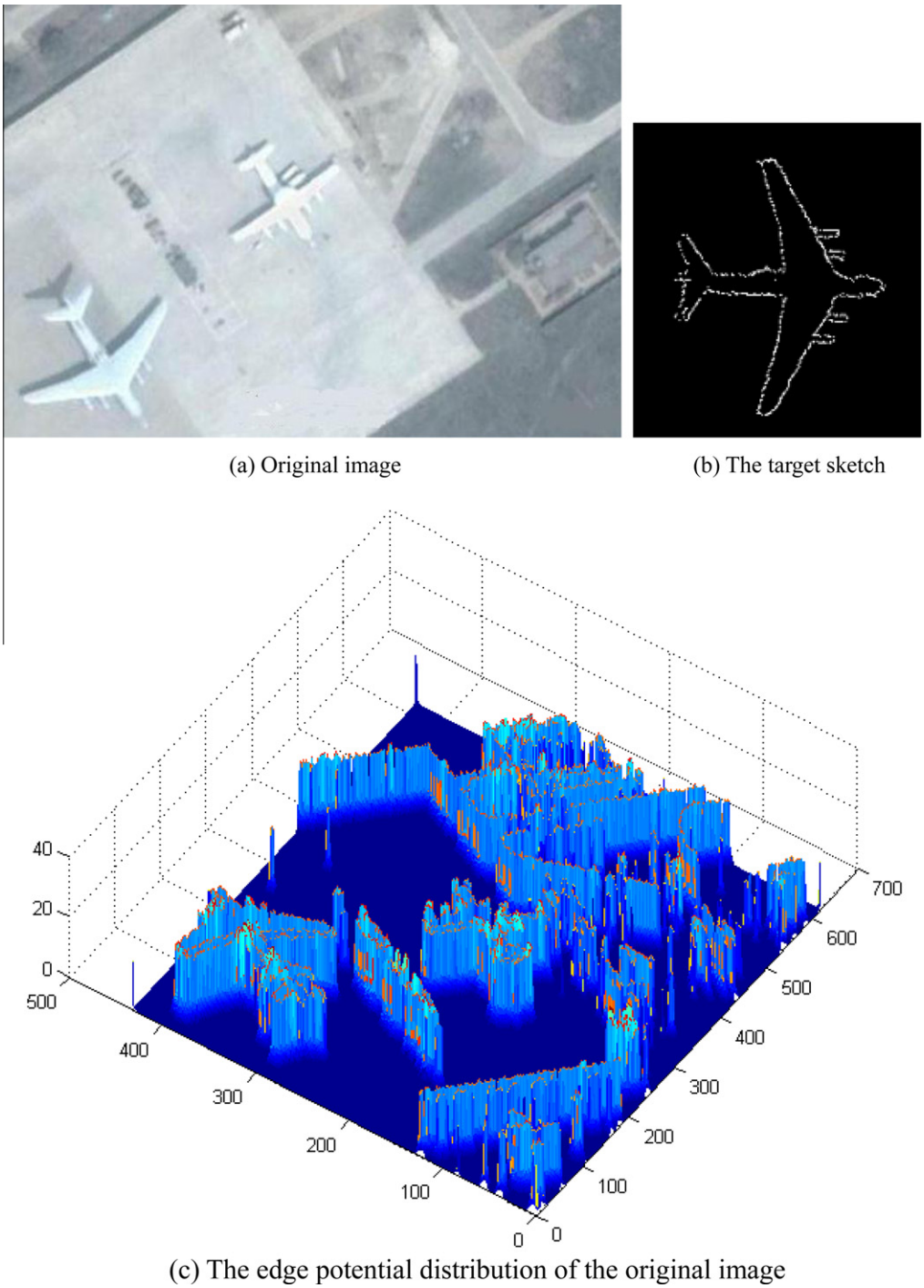
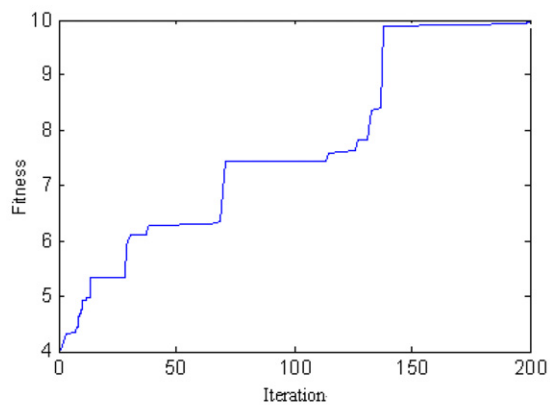


Fig. 7. Experimental results of Case 4 by using our proposed method. (a) Original image, (b) the target sketch, (c) the edge potential distribution of the original image, (d) the results of target recognition and (e) the evolution curve of the ABC optimization algorithm.

(d) The results of target recognition



(e) The evolution curve of the ABC optimization algorithm

Fig. 7 (*continued*)

Step 2 According to the binary edge distribution of the target image and the practical edge potential field function model shown in Eq. (3), calculate the EPF distribution of the target image.

Step 3 Initialize the parameters of artificial bee colony optimization algorithm, such as the population of the bee colony N_s, the number of employed bees N_e and the number of the unemployed bees N_u, which satisfy the condition shown as follows:

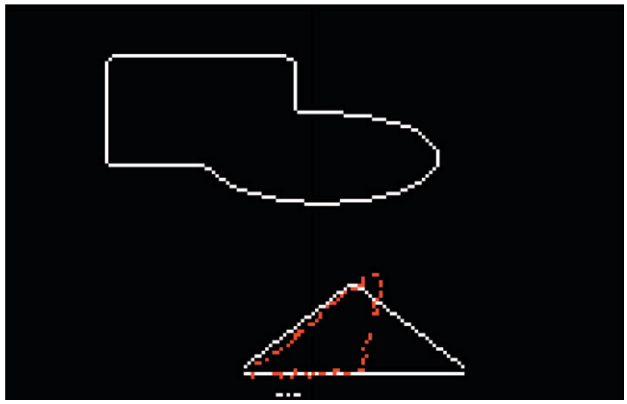
$$N_s = N_e + N_u \tag{13}$$

Obviously, a larger N_s will contribute to a larger possibility of finding the best solution of the problem, however, it also means an increased computing complexity of the algorithm. In general, we define $Ne = Nu$, and according to our special problem, we set $Ns = 200$. Denote the largest searching times with *Limit* (50 in our experiments), current iterations with T, and the largest iterations with $T_{\max}$. Initialize the population of geometric transformation parameters, which include the horizontal translation parameter t_x, the vertical translation parameter t_y, the rotation angle parameter *angle*, and the scaling parameter *scale*. By considering these operators $c = (t_x, t_y, angle, scale)$, the original sketch is iteratively roto-translated and scaled obtaining different instances of it, which are fitted within the potential field to compute a matching index. The goal is to find the optimal combination of parameters, which can provide the best fitness, and to evaluate if the relevant matching index is high enough to determine with a certain degree of confidence the presence of the model in the target image. Initialize the search time of each bee $Bas = 0$, and the starting iteration $T = 1$.

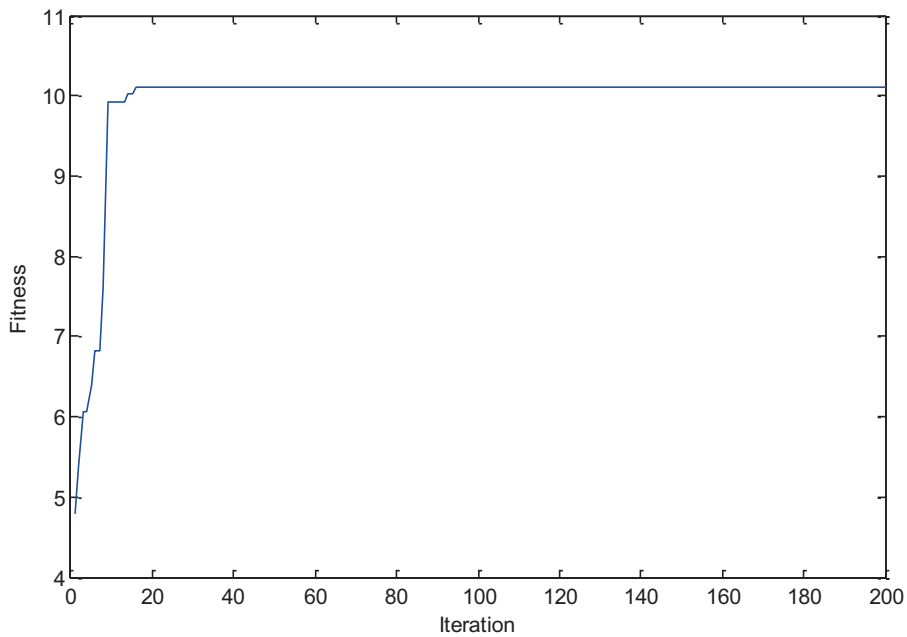
Step 4 According to the geometric parameters of the employed bees, calculate their similarity values respectively based on the defined similarity function as shown in Eq. (5):

$$f(c_k) = \frac{1}{N^{(c_k)}} \sum_{n^{(c_k)}=1}^{N^{(c_k)}} \left\{ EPF\left(x_n^{c_k}, y_n^{c_k}\right) \right\} \tag{14}$$

where $c_k = (t_x, t_y, angle, scale)$ is the geometric operator on the kth iteration, $N^{(c_k)}$ represents the number of edge points of the target image contained in the mask image contour under the geometric operator c_k, while $(x_n^{c_k}, y_n^{c_k})$ are their corresponding vertical and horizontal coordinates, and $n^{(c_k)}$ denotes the nth edge point. According to Eq. (5), $f(c_k)$ shows the average potential value calculated along the contour of the mask image, and accordingly,



(a) Experimental result by using GA



(b) Evolution curve of GA

Fig. 8. The target recognition results by using GA. (a) Experimental result by using GA and (b) evolution curve of GA.

when the fitness function $f(c_k)$ achieves its maximum value, we find the best solution to match the target image.

Step 5 The employed bees search around their current positions to find new solutions, and update their positions if the new fitness value is higher than the original value.

Step 6 The unemployed bees apply the roulette selection method to choose the bee individual that possesses a relatively good fitness value as the leading bee, according to the calculated fitness results of employed bees.Each recruited unemployed bee continues to search new solutions just around the leading bee's solution space, and calculate their fitness values. If the value of the new solution is better than the original value, the unemployed bee converts into an employed bee, which means that update the positions of the employed bees, and continue exploring with *Bas* re-initialized as 0, or else, keep searching around, and its *Bas* value plus one.

Step 7 If the search times *Bas* is larger than certain threshold *Limit*, the employed bee gives up the solution, and research the new food resources, which is realized by re-initializing the geometric parameters and calculating the fitness value.

Step 8 Store the best solution parameters and the best fitness value.

Table 1
The comparative results using our proposed approach and GA.

Our proposed approach		GA	
Best fitness	Best parameters	Best fitness	Best parameters
11.262	**[78, 68, 331, 1.2]**	**11.262**	**[78, 68, 331, 1.2]**
11.262	**[78, 68, 331, 1.2]**	**11.829**	**[79, 69, 328, 1.2]**
11.262	**[78, 68, 331, 1.2]**	**11.262**	**[78, 68, 331, 1.2]**
11.908	**[79, 69, 330, 1.2]**	10.268	[81, 65, 189, 0.8]
11.272	**[79, 65, 329, 1.3]**	**10.792**	**[79, 68, 332, 1.2]**
10.5326	[79, 66, 331, 1.2]	9.679	[87, 67, 329, 0.8]
11.262	**[78, 68, 331, 1.2]**	**11.262**	**[78, 68, 331, 1.2]**
10.8506	**[80, 67, 333, 1.3]**	9.282	[77, 88, 116, 0.9]
11.262	**[78, 68, 331, 1.2]**	10.5153	[77, 73, 187, 0.9]
11.262	**[78, 68, 331, 1.2]**	**11.262**	**[78, 68, 331, 1.2]**
11.262	**[78, 68, 331, 1.2]**	**10.832**	**[78, 67, 331, 1.2]**
10.792	**[79, 66, 332, 1.2]**	8.679	[87, 67, 329, 0.8]
10.6231	[80, 97, 115, 0.8]	10.597	[79, 67, 193, 0.8]
11.262	**[78, 68, 331, 1.2]**	10.099	[79, 68, 329, 1.2]

(a) The target recognition result by using GA for Case 2

(b) The target recognition result by using GA for Case 3

(c) The target recognition result by using GA for Case 4

Fig. 9. Series target recognition results by using GA. (a) The target recognition result by using GA for Case 2, (b) the target recognition result by using GA for Case 3 and (c) the target recognition result by using GA for Case 4.

Step 9 If $T < T_{\max}$, go to Step 5. Otherwise, output the optimal parameters and optimal fitness value.

The detailed procedure can also be shown with Fig. 3.

5. Experimental results and analysis

In order to investigate the feasibility and effectiveness of the proposed method in this work, series of experiments are conducted, and further comparative experimental results with the GA method is also given.

The initial parameters of ABC algorithm were set as: $Ns = 50$, $Ne = 25$, $Nu = 25$, $T_{\max} = 200$, $Limit = 50$.

The first experiment (Case 1) is to find an isosceles triangle among a variety of shapes in the original image. After a 330 degree rotation, 1.2 times scaling, and a [78, 68] translation, the target can be successfully recognized in the image, which means that the best geometric parameters are [78, 68, 330, 1.2]. The experimental results are shown in Fig. 4.

The task of the Case 2 is to find a target plane in the airport, and the results are shown in Fig. 5. And Fig. 6 and Fig. 7 are target recognition results of Case 3 and Case 4 respectively.

Obviously, the results of all the experiments show that our proposed method can recognize the exact positions of targets in the image through the operations of rotation, scaling and translation.

To compare our identification effect with other approaches, more experiments are conducted by using GA. The results using GA are shown in Fig. 8.

From Fig. 8, the evolution curve of GA is trapped into stagnancy (local best) from the 20th iteration, while our proposed ABC optimized EPF approach can avoid the local best easily. Furthermore, Table 1 displays in detail the performance comparison of our proposed approach and the traditional GA with 14 times experiments.

From the above experimental results, it is clear that our proposed ABC optimized EPF approach is superior to the traditional GA in solving the target recognition problem for aircraft at low altitude.

Beside, in the following Fig. 9 the recognition results of Cases 2–4 by using GA are shown, which all contribute to our conclusion that our proposed ABC optimized EPF approach performs better than GA.

6. Concluding remarks

As the target recognition for aircraft at low altitude is rather complicated, a novel ABC optimized EPF approach to target identification for aircraft at low altitude is proposed in this paper. This hybrid method takes advantages of the accuracy and stability for EPF in target shape recognition, and ABC algorithm is adopted to optimize the matching parameters. Series of experiments are conducted, and experimental comparison results between the proposed method and the traditional GA are also given to verify the feasibility and effectiveness of our proposed ABC optimized EPF approach, which provide an more effective way for target recognition for aircraft with low altitude.

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