Chaotic Mutated Bat Algorithm Optimized Edge Potential Function For Target Matching

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***Abstract*—In this paper, we present a novel edge based matching approach to target recognition. To recognize the marker on a rotorcraft, a chaotic mutated bat algorithm optimized edge potential function approach is proposed to accomplish the matching between the sketch image and the scene in real applications. A novel type of attractive contour pattern is acquired using the edge potential function. These edge structures can be conveniently exploited for target matching. Bat algorithm is adopted for the optimization problem of searching the optimal match in the scene, and a chaotic mutated bat algorithm is proposed using the chaotic theory and a mutated operator. Thus, the target matching task is converted to optimizing the average of potential value by the processing of translating, reorienting and scaling the sketch image. Series of experiments are conducted to show that our method is superior to other methods. Our proposed method can achieve the higher fitness value over the standard optimization algorithms.**

Keywords—bat algorithm; chaotic mutated operator; edge potential function; target matching

I. Introduction

In the tasks of reconnaissance and search, target recognition is a key issue to achieve autonomous capture for aircraft. Target representation and matching [1] is a very important aspect, and has been extensively used for practical problem [2]. In order to obtain accurate identification results in real applications, the target recognition method must be efficient and stable.

Generally, similarity measuring and feature extraction are two basic processes for target matching and recognition. For similarity measuring, template matching is widely used in object detection and object tracking. Image match involves the translation of the template to every possible position in the test image, and the evaluation of a measure of the match between the template and the source image at that position. Some optimization algorithms are proposed to obtain good results for template matching [3] or edge extraction [4]. For target representation, the edge-based feature can be more robust and easily extracted [5]. Edge potential function (EPF) is proposed as a similarity evaluating measure and a new approach to the image retrieval [6]-[7]. Based on this measure, extended methods have been proposed for target recognition [8]-[10]. The concept of EPF is derived from the potential generated by charged particles and a sort of attraction field can be represented by using EPF to attract a user sketch in the position where a similar shape is present in the image. In target matching, the higher the similarity of the two shapes, the higher the edge potential value.

Bat algorithm (BA) is a new swarm intelligence optimization method inspired by the bat's behavior [11]. Most bats use echolocation at a certain degree for navigation, communication and foraging. Inspired by the behavior of bats with varying pulse rates of emission and loudness, BA has been proved to possess a better performance compared with other algorithms like genetic algorithm (GA) and particle swarm optimization (PSO) algorithm [12]-[14].

In this paper, a type of attractive contour pattern is acquired using EPF to model the attraction of edge structures. The potential value can be conveniently exploited for target matching. BA is adopted for the optimization problem of searching the optimal match in the scene. An improved chaotic mutated bat algorithm (CMBA) is proposed based on the chaotic theory and mutation operator. Then, the best solution is generated by the translation, rotation and scale operations to maximize the potential value of the sketch image. Our proposed method is described in Section 2, followed by implementation details including the flowchart in Section 3. Experimental results and conclusions are given in Section 4, and Section 5, respectively.

II. Chaotic Mutation Bat Algorithm

The core to our edge-based matching algorithm is to formulate the whole image matching process as an optimization problem. This process includes estimating the edge potential function and searching the optimal match. EPF and BA are first introduced. Then the extended algorithm is described with the chaos theory and mutated operator.

A. Edge Potential Function (EPF)

As a newly-developed similarity evaluating measure, EPF is derived from the potential generated by charged particles[6]. In general, the edge potential value is calculated from an edge map of an image. The attraction field is generated by those charged edge points to represent the edge potential.

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To reduce the local edge activity connected to noise and textures, and limit the impact of dense edge areas on the potential field, the windowed EPF model was also outlined to simplify the calculations and improve the robustness of target-matching in cluttered environments [7]. Using the slide-window detector, the windowed EPF ignores those edge points outside a predefined window W. It can be expressed as

$$EPF(p) = \frac{Q}{4\pi\varepsilon_{eq}} \sum_{p_i \in W} \frac{1}{\|p - p_i\|^2} \tag{1}$$

where ε_{eq} is a constant, and Q is equal to the charge of each edge point $Q_{eq}(x_i, y_i)$ to simplify the assumption. In our experiments, we set Q to 1, ε_{eq} to 0.05 and the window size to 5×5. When using EPF as a similarity measure, the searched target to be matched can be considered as a test object. An image containing a single shape is expected to be attracted by a set of equivalent charged points and used as a sketch image. The test image is the selected scene. Then the similarity measuring problem between the searched object and visual objects is converted to maximize the total attraction engendered by the edge field.

To avoid the large computational time in real applications, the saliency based edge is utilized. A global saliency measure based on the spectral residual is proposed to favor regions with an unique appearance within the entire image [15]. However, this measure is conducted at a certain scale, which is hard to be extended in different scenes. In this paper, the multi-scale saliency based edge of a test image is extracted by extend the spectral residual to multiple scales[16]. Based on this, we define the saliency based edge for every edge pixel p as

$$SE(p) = \sum_{\{p \in w_S | I_S(p) \geq \theta_S\}} I_S(p) \times \frac{|p \in w_s \,|\, I_S(p) \geq \theta_S|}{|w_S|} \tag{2}$$

where $I_S(p)$ is the spectral residual calculated as [15], w_S is the window, θ_S is the scale-specific threshold, and the operator $|\cdot|$ indicates the number of pixels in a window. The parameters in this paper are adopted as [16]. This multi-scale saliency can measure the uniqueness characteristic at different scales, which reduces a large amount of edge points in test scenes.

B. Bat Algorithm (BA)

Inspired by the bat's echolocation behavior, BA is proposed as a metaheuristic search algorithm [11]. As well as the other optimization algorithms, this algorithm use some idealized rules on the analogy of behavior as follows:

(1) All bats utilize echolocation to sense the distance and surroundings;

(2) At position x_i, bats fly randomly with some characteristics such as velocity v_i, frequency f, varying wavelength λ and loudness A_0. The wavelength (or frequency) is spontaneously accommodated. The rate of pulse emission can be adjusted within the range $r \in [0,1]$ depending on the proximity of their target. The loudness varies from a minimum constant $A_{\min}$ to a large one A_0.

Some simplifications are also considered in this algorithm. No ray tracing is used in estimating the time delay and 3-D topography, as it is more computationally extensive in multidimensional cases. As higher frequencies have short wavelengths and travel a shorter distance, for simplicity, the frequency is limited to the range of $[0, f_{\max}]$ and the rate of pulse can simply be in the range of $[0,1]$.

In BA, each bat is defined by its position x_i, velocity v_i, frequency f_i, loudness A_i and the emission pulse rate r_i. The new solutions x_i^t and velocities v_i^t at time step t are updated with frequency f_i by the following equations $(i = 1, 2, ..., N)$

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \tag{3}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x^*) f_i \tag{4}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{5}$$

where $\beta \in [0,1]$ is a random vector drawn from a uniform distribution, x^* is the current global best location (solution) which is located after comparing all the solutions among all the bats. Initially, each bat is randomly given a frequency within the predetermined range $[f_{\min}, f_{\max}]$.

At the local search part, the random walk operation is used. Once a solution is selected as the best one, a new solution is generated for each bat by:

$$x_{new} = x_{old} + \varepsilon A^t \tag{6}$$

where $\varepsilon \in [-1,1]$ is a random scaling factor, and A^t is the average loudness of all bats at step t.

In fact, the update strategies of velocity and position have some similarities to the procedures of other optimization algorithms. In BA, f_i controls the pace and range of the movement of swarms and α is similar to the cooling factor of a cooling schedule. In fact, BA is a balanced combination of the standard PSO and an intensive local search strategy.

C. Chaotic Mutated Bat Algorithm (CMBA)

In this part, we extend the standard bat algorithm with the chaos theory and mutated operator. Chaos theory is epitomized by the so-called butterfly effect detailed by Lorenz [17]. The chaotic sequence is mapped according to the logistic equation $x_{n+1} = 4x_n(1 - x_n)$, where $0 < x_n < 1$. The basic characteristic of chaos is to generate the large difference in its long-time behavior through a very small difference in the initial value. Therefore, the ergodicity and irregularity of the chaotic variable is utilized to conduct the chaotic search in the

neighborhood of the current optimal one, which is capable to help the algorithm jump out of the local optimum and find the global optimal parameters.

To improve the search efficiency and speed up the convergence, a mutated operator derived from differential evolution [18] is introduced into our algorithm to increase diversity of the population. Once a solution is selected among the current best solutions at the local search part in Eq.6, the update procedure is selected based on the magnitude of random number. If $rand > r_i$, a new solution for each bat is generated locally using the random walk operator; otherwise, the mutated operator is used to update the new solution to improve the search efficiency by

$$x_{new} = x_{r_1}^t + \kappa(x_{r_1}^t - x_{r_1}^t) \tag{7}$$

where κ is the mutation weighting factor and we set $\kappa = 0.5$ in this paper, r_1, r_2, r_3 are uniformly distributed random integer numbers between 1 and bats number N. For simplification and speeding up convergence, we use fixed loudness A and pulse rate r instead of various parameters in Eq.7. In this paper, we set loudness A to 0.7 and pulse rate r to 0.6 in our experiments.

III. Implementation

The implementation procedure of our proposed approach to target matching can be described in Fig.1.

In our experiments, the initial parameters of our CMBA are set as: N=30, A =0.7, r =0.6, T_{max}=200. All experiments are performed using MATLAB 7.14.0(R2012a) on a PC with Core Ⅱ 2.4GHz CPU and 3G RAM.

IV. Results

To verify the effectiveness of our proposed method, series of experiments are conducted. Comparative experimental results with the standard BA and PSO are also given.

We first test our multi-scale saliency based edge extraction method in real scenes. In those images captured from these scenes, the black marker is pasted on the rotorcraft. Our goal is to recognize the marker accurately. Fig.2 reports performance for saliency detection methods. The region with deepest color indicated the most salient object. Both our multi-scale saliency method and the spectral residual method can find the entire object, while our method concentrates better on the marker.

After applying the multi-scale saliency method to input images, we extract edge points using the canny operator. Fig.3 shows that our multi-scale saliency based edge map contains less background information except the marker. Thus, this process reduces the search region for target matching.

Experiments using our CMBA optimized EPF method are then conducted for detecting the marker on rotorcraft. The comparative experimental results are shown in Fig.4-Fig.7. We test our methods in two cases. Targets with their edge potential distribution maps in these cases are the same, which are shown in Fig.4(a) and Fig.4(b). In Case 1, the distance is close and there are rotation and scale changes. We perform the experiment using the CMBA, in comparison with the standard BA and PSO. Matching results with three optimization methods are shown in Fig.4(c). Fig. 5 reports comparative results of three evolution curves.

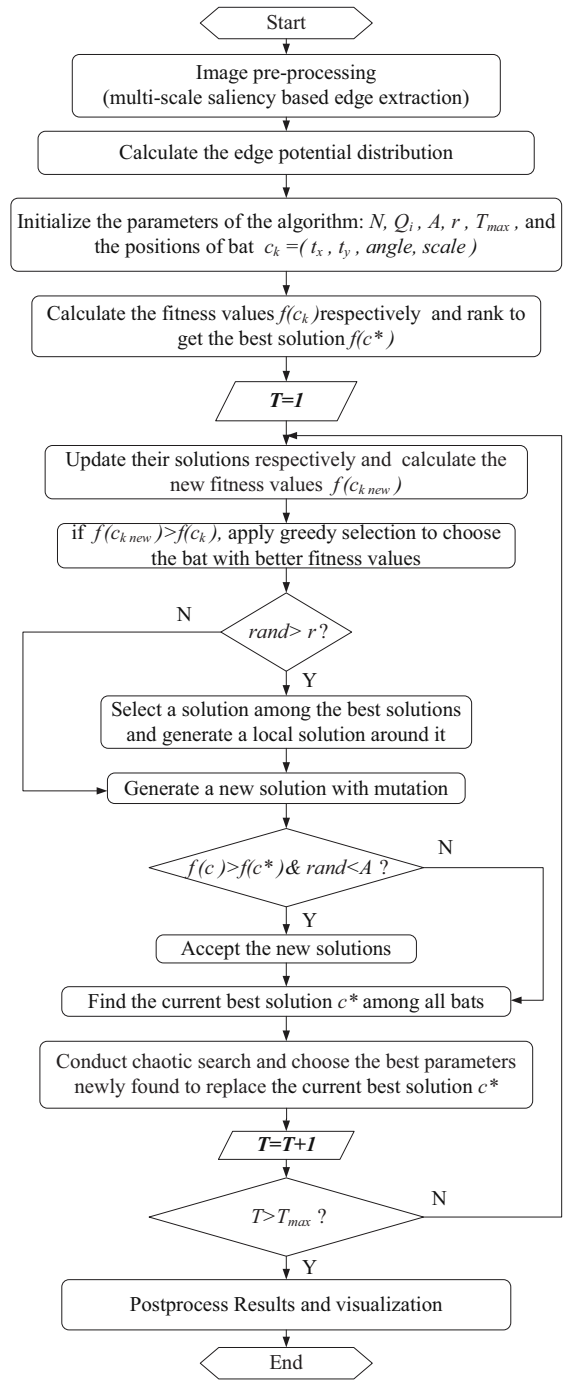
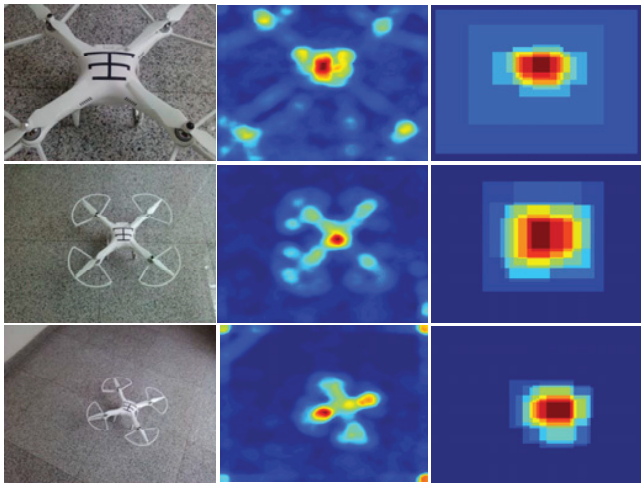
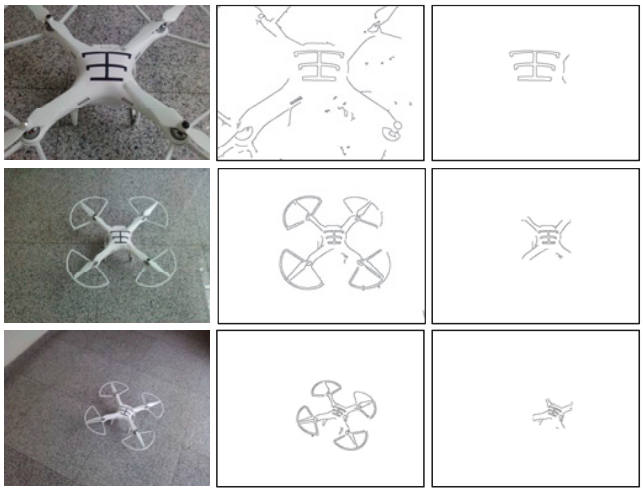


Fig. 1. Procedure of our CMBA optimized EPF method



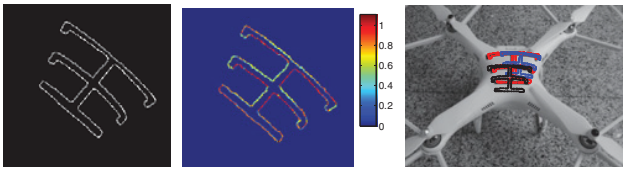
(a) (b) (c)

Fig. 2. Comparative results of saliency detection: (a)original image; (b) spectral residual; (c)multi-scale saliency



(a) (b) (c)

Fig. 3. Comparative results of edge detection: (a)original image; (b)canny operator; (c) multi-scale saliency based edge



(a) (b) (c)

Fig. 4. Matching results in Case 1: (a)target contour; (b)edge potential distribution map; (c)matching results with CMBA (red), BA(blue) and PSO(black),respectively

From these results we can see that our proposed method can recognize the exact position of the marker in the real scene through operations of rotation, scaling and translation. Comparative results of three evolution curves in Fig.5 indicate

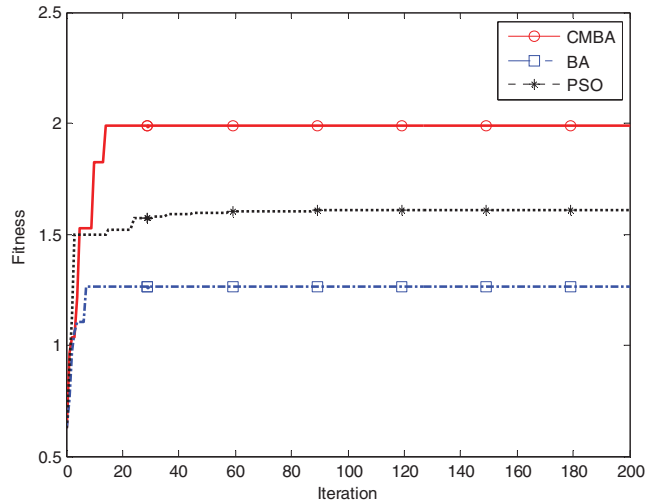


Fig. 5. Comparative results of three evolution curves in Case 1

(a) (b) (c)

Fig. 6. Matching results in Case 2 using three methods: (a)CMBA; (b)BA; (c)PSO

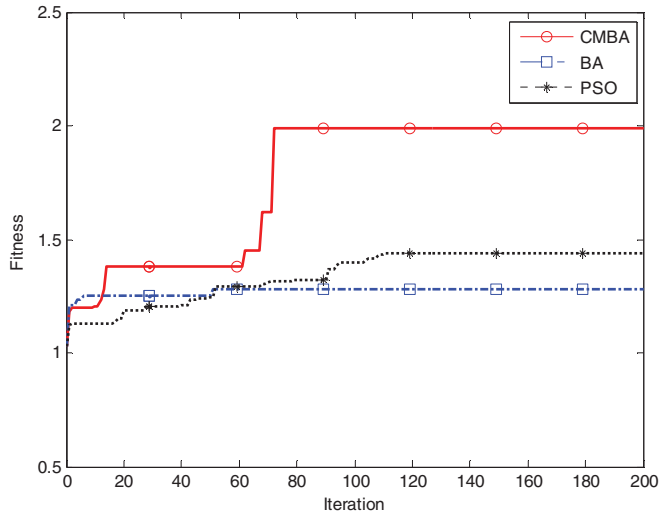


Fig. 7. The evolution curves of three algorithms in Case 2

that our methods can obtain better matching result than the standard BA and PSO.

In Case 2, the distance is further, thus the target looks smaller. We also perform the comparative experiments using three methods. Matching results and evolution curves are shown in Fig.6 and Fig.7, respectively. These results show that our method is superior to other methods even though the target is small.

In these two cases, the initialization parts of three optimization methods are the same. The same initial population can avoid the effect of different initialization. The population size and iteration number are also consistent. All experimental results show that our proposed method outperforms the standard BA and PSO. There is a need to note that, as the limit of matching measure, our method is easily disturbed by the noise and discrete edge points. The computation time of our method is also larger than the others, since more operations are utilized.

V. Conclusions

In this paper, a novel CMBA optimized EPF approach to target matching is proposed. Our proposed method is capable to combine the accuracy and stability of EPF in target shape recognition and the search capability of extended CMBA for optimizing the matching parameters. Series of experiments in real applications are conducted. Comparative results are given to verify the feasibility of our proposed method, which provides a more effective way for target matching.

Acknowledgment

This work was partially supported by National Natural Science Foundation of China under grant #61425008, #61333004 and #61273054, and Aeronautical Foundation of China under grant #20135851042.

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