Biological edge detection for UCAV via improved artificial bee colony and visual attention

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Abstract

Purpose – The purpose of this paper is to propose a biological edge detection approach for aircraft such as unmanned combat air vehicle (UCAV), with the objective of making the UCAV recognize targets, especially in complex noisy environment.

Design/methodology/approach – The hybrid model of saliency-based visual attention and artificial bee colony (ABC) algorithm is established for edge detection of UCAV. Visual attention can extract the region of interesting objects, and this approach can narrow the searching region for object segmentation, which can reduce the computational complexity. An improved ABC algorithm is applied in edge detection of the salient region.

Findings – This work improved ABC algorithm by modifying the search strategy and adding some limits, so that it can be applied to edge detection problem. A hybrid model of saliency-based visual attention and ABC algorithm is developed. Experimental results demonstrated the feasibility and effectiveness of the proposed method: it can guarantee efficient target localization, with accurate edge detection in complex noisy environment.

Practical implications – The biological edge detection model developed in this paper can be easily applied to practice and can steer the UCAV during target recognition, which will considerably increase the autonomy of the UCAV.

Originality/value – A hybrid model of saliency-based visual attention and ABC algorithm is proposed for biological edge detection. An improved ABC algorithm is applied in edge detection of the salient region.

Keywords Biological edge detection, Artificial bee colony, Unmanned combat air vehicle, Visual attention

Paper type Research paper

Introduction

Unmanned combat air vehicle (UCAV) will play an important role in future aerial warfare (Duan *et al.*, 2010b, 2011). Compared with current manned platforms, UCAVs are more affordable and suitable for high-risk missions (Wise, 2003; Zhang *et al.*, 2010), with some unique advantages such as a larger combat radius, greater payload, lower observability and higher manoeuvrability (Pradeep, 2002; Zhao and Lu, 2012).

One of the main challenges of UCAV design is the automatic target recognition system. Inaccurate detection information will usually directly affect the awareness of the UCAV about the battlefield state and target selection. Moreover, uncertain detection information usually influences the recognition system with side effects. In recent years, many methods for air vehicle systems have been proposed to improve the performance of target recognition. A novel shape-matching approach with optimized edge potential function is proposed as an effective alternative to visual target recognition (Xu *et al.*, 2010). 3D local map and vehicle pose are used to improve the ability to robustly visual lock on to the ground targets (Min *et al.*, 2012). What is more, visual detection with ground targets search and assignment were also providing a progress and alternative for UACV (Liu *et al.*, 2012; Bertuccelli and Cummings, 2012; Lin *et al.*, 2012). In this work, we will focus on UCAV automatic target recognition, and only the edge detection will be studied. Edge detection is the fundamental step in edge extraction and object delineation in image processing. The goal of edge detection is to mark the points which contain the major information in a digital image. An effective edge detector can reduce a large amount of data and still keep most of the important feature of the image or object. Many edge detection algorithms have developed based on computation of the intensity gradient vector at which the intensity changes sharply.

In our work, a hybrid biological model of saliency-based visual attention and improved artificial bee colony (ABC) algorithm will be emphasized. The main objective of our work is to design an edge detection approach for aircraft such as UCAV, with the objective of making the UCAV recognize targets, especially in complex noisy environment. ABC algorithm is a new swarm intelligence meta-heuristic optimization method, based on the intelligent foraging behaviour of honey bee swarm (Karaboga, 2005).

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ABC algorithm is usually used for optimizing multi-variable multi-modal numerical functions and has been proved to outperform the other algorithms in function optimization problem such as genetic algorithm (GA), differential evolution (DE) algorithm, particle swarm optimization (PSO) algorithm and particle swarm inspired evolutionary algorithm (PS-EA) (Karaboga and Basturk, 2007, 2008; Karaboga and Akay, 2009). ABC algorithm conducts local search in each iteration, and the probability of finding the optimal results is significantly increased, which can efficiently avoid local optimum to a large extent. This work improved ABC algorithm by modifying the search strategy and adding some limits, so that it can be applied to edge detection problem.

Saliency-based visual attention model created by Itti is a successful bottom-up computational model (Itti *et al.*, 1998, 2001). It can help select regions of an image that contain salient objects, which can be used for the task of object fast recognition in the visual field. The original model is to obtain the features maps of different feature channel like color, intensity and orientation. Some improved work on the attention model has been done to make the model more accurate and efficient (Siagian and Itti, 2007; Parikh *et al.*, 2010; Li *et al.*, 2011). More features channels such as flicker, motion, stereo disparity have been added to the model based on the different detecting tasks. The work to compute the gain or weight of particular maps also can make the result more approximate to the feel of people.

In this paper, the visual attention model is to get the region of object recognition. ABC algorithm is introduced to solve the object edge detection problem, whose aim is to extract the object edge information in the salient region. Experimental results demonstrated the feasibility and effectiveness of the proposed method, and it can guarantee an efficient target localization, with accurate edge detection in complex noisy environment.

Model development

In this section, the mathematical model of biological method of saliency-based visual attention and ABC algorithm is developed.

Saliency-based visual attention

Visual attention is an important psychological adjustment mechanism of human vision. Bottom-up visual attention is the process by which primates quickly select regions of an image that contain salient or conspicuous objects. The saliency-based visual attention model is to compute a saliency map which indicates how conspicuous every location of the target in the input image is. In the saliency model (Figure 1) proposed by Itti (Itti *et al.*, 1998), an image is analyzed along multiple low-level feature channels to give rise to multi-scale feature maps, which detect potentially interesting local spatial discontinuities using simulated center-surround neurons. In the saliency-based visual attention model, first, three features are extracted from the image after linear filtering. The feature channels are used to simulate the neural features which are sensitive to color (red/green and blue/yellow), intensity (dark and bright) and orientation (0°, 45°, 90° and 135°).

Second, the multi-scale approach is aimed at detecting conspicuous features of different sizes to produce a set of images using imaging pyramids operator. Each feature channel is computed to obtain multi-scale feature maps using pyramids and center-surround operations. The scales of each channel are obtained from pyramidal filter outputs (Gaussian pyramids for the color and intensity channels and Gabor filters for the orientation channel), from scale 0 (the original image) to scale 8 (the image reduced by the ratio of 1:256 in both horizontal and vertical dimensions). Then the model performs center-surround operations between filter output maps. This operation combines center scales ($c = \{2, 3, 4\}$) and surround scales ($s = c + d$) with center-surround scale differences ($d = \{3, 4\}$).

After the center-surround operation, the scale pairs (2_5, 2_6, 3_6, 3_7, 4_7, 4_8) are obtained. Then all the feature maps are combined into three conspicuity maps (color, intensity and orientation). In order to combine different feature maps, all feature maps are resampled to scale 4 which is 1/16 the size of the original image and normalized into [0, 1]. Thus, three conspicuity maps are obtained through across-scale addition, which consists of reduction of each map to scale 4 and point-by-point addition.

The three normalized conspicuity maps are then linearly summed and their average forms the final salience map. From the final salience map, the most salient region can be obtained in the visual field.

Improved ABC algorithm for edge detection

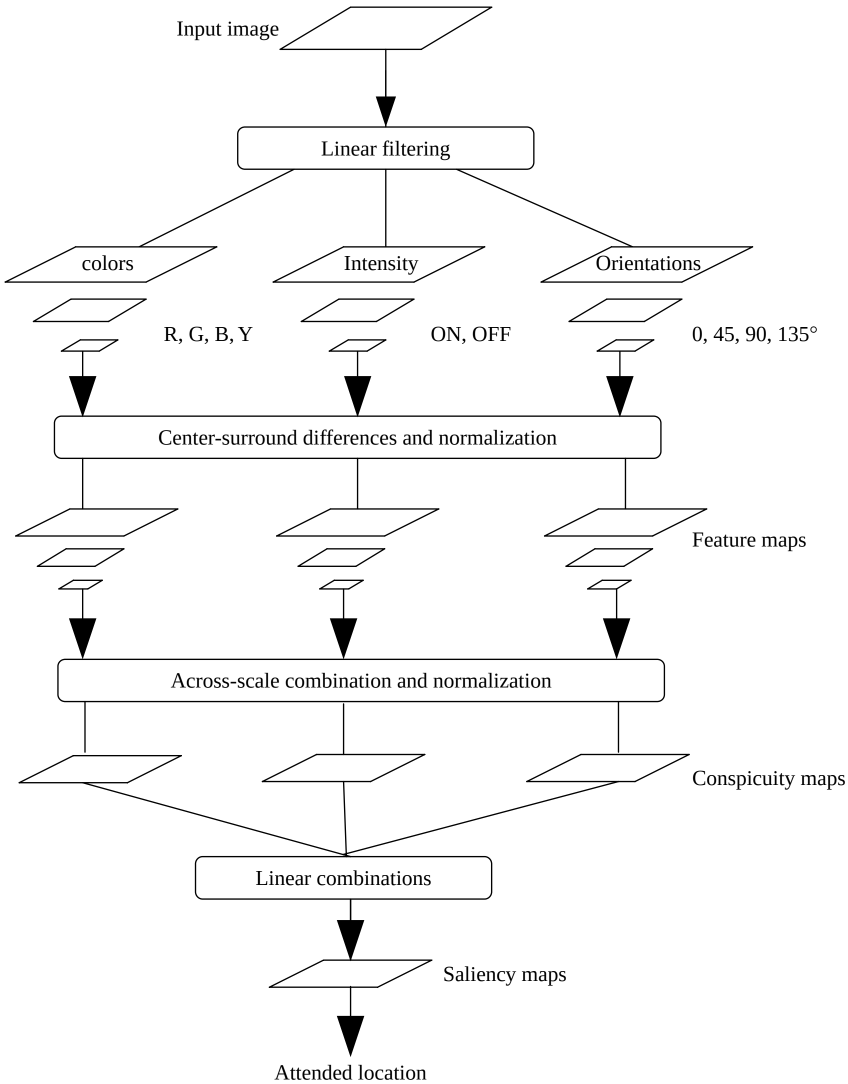
ABC algorithm consists of three essential components: employed and unemployed artificial foraging bees, and artificial food sources. Employed and unemployed foraging bees search for rich food sources, which is to get out the good solutions for a given problem. In the ABC algorithm, the colony of artificial foraging bees contains three groups of bees: employed bees, onlookers and scouts. The model of ABC algorithm also defines two leading modes of behaviour which are necessary for self-organizing and collective intelligence: recruitment of foraging bees to rich food sources resulting in positive feedback and abandonment of poor sources by foraging bees causing negative feedback.

The value of a food source (A and B in Figure 2) depends on many factors. However, for the sake of simplicity, the "profitability" of a food source can be represented with a single quantity in the ABC algorithm (Karaboga, 2005). In edge detection, the position of a food source represents a possible parameters solution to the optimization problem and the nectar amount of a food source corresponds to the similarity value of the associated solution. The rich food sources are the marked points of which the edge of the image or object is composed.

It is assumed that if a bee has no knowledge about the food sources in the search field, bee initializes its search as an unemployed forager (Duan *et al.*, 2010a; Xu *et al.*, 2010). Unemployed foragers are continually looking out for a food source to be exploited. There are two types of unemployed foragers: scouts (S in Figure 2) and onlookers (R in Figure 2).

For every food source, there is only one employed bee. The number of employed bees is equal to the number of food sources. They are associated with a particular food source which they are currently exploiting. 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

Figure 1 Overview of saliency-based visual attention model



source, it returns to the hive and unloads the nectar to the food area in the hive. Three possible options related to residual amount of nectar for the foraging bee (i.e. UF, EF1 and EF2 in Figure 2). In this way, the bees can construct a relative good solution of the multi-modal optimization problems.

At the initial moment, all the bees without any prior knowledge play the role of detecting bees. After a random search for bee sources, the detecting bees can convert into any kind of bees above in accordance with the profit of the searched food sources. The changing rules are described as follows.

When the profit of the food source the bee searched is higher than the threshold, it becomes a leading bee, going on exploring nectar and also recruiting more bees (EF1) to explore together. When the profit of related food source is relative low, it gives up the food source, and again becomes a detecting bee to search for new food source (UF). When the profit is less than certain threshold, it follows leading bees to explore nectar. When searching times around hive exceed a certain limit but the bees still could not find a good resource, the bees abandon the source and find a new one.

To apply ABC algorithm, the considered optimization problem is first converted to the problem of finding the best parameter vector which minimizes an objective function. Then, the artificial bees randomly discover a population of initial solution vectors and then iteratively improve them by employing the strategies: moving towards better solutions by means of a neighbour search mechanism while abandoning poor solutions.

The procedure of our improved ABC algorithm approach to image edge detection can be explained as follows.

Section 1

Step 1. Image pre-processing. Obtain the image and convert it into grayscale format. Then filter the target image to remove the noise.

Step 2. Initialization of parameters. Initialize the parameters of ABC algorithm, such as the population of bee colony N_s, the number of employed bees N_e and unemployed bees N_u and so on.

In general, we define $N_s = N_e + N_u$, and $N_e = N_u$. Obviously, larger N_s will contribute to a larger possibility of

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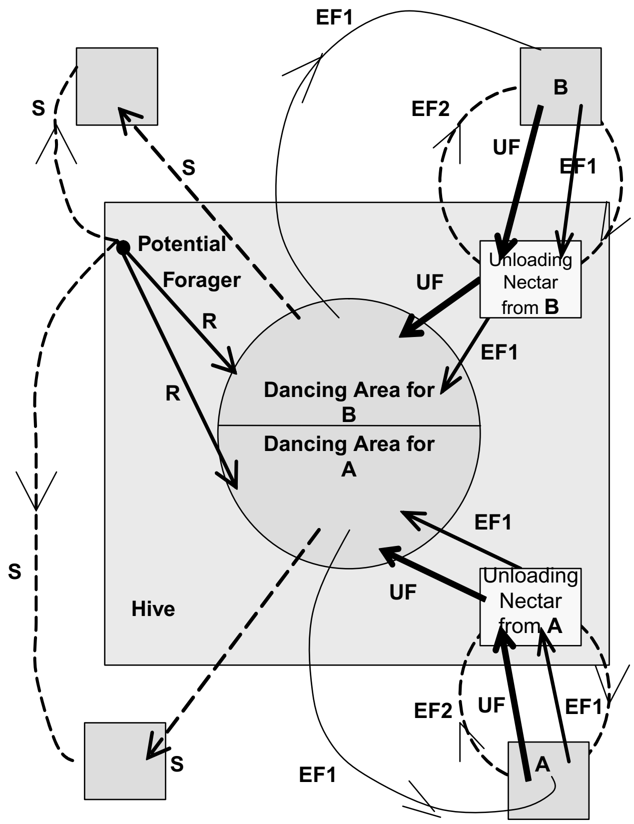
Figure 2 Behaviours of honey bees foraging for nectar



finding the best solution of the problem; however, it also means an increased computing complexity of the algorithm.

Step 3. Search the food sources. Send all colony bees to search the food sources randomly. Then calculate the fitness value of each food source based on the fitness function. These food sources form the image edge which we want to be detected. The larger the fitness value is, the better the image edge detects.

In this paper, the fitness function is shown as:

$$\begin{aligned} f(i,j)=&|I_{i-2,j-1}-I_{i+2,j+1}|+|I_{i-2,j+1}-I_{i+2,j-1}|+|I_{i-1,j-2} \\ &-I_{i+1,j+2}|+|I_{i-1,j+1}-I_{i+1,j-1}|+|I_{i-1,j}-I_{i+1,j}| \\ &+|I_{i,j+1}-I_{i,j-1}|+|I_{i+1,j-2}-I_{i-1,j+2}|+|I_{i+1,j+1}-I_{i-1,j-1}| \end{aligned} \quad (1)$$

Formula (1) is to calculate the gradient of the variation of the image's intensity values on the clique (a square of 5*5 as shown in Figure 3) (Tian *et al.*, 2008). $I_{i,j}$ is the intensity value of the pixel at the position (i, j) of the image.

Step 4. Initialization of the positions of the employed bees. Sort descending the fitness values of the food sources in Step 3. Then select the number of the former N_e as the positions of the employed bees.

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

The search strategy can be described as follows: for the ith employed bee, first engender a random integer j between 1 and D and a random integer k between 1 and N_e, then the jth parameter of the ith employed bee could be updated by:

$$y_i'(j)=y_i(j)+(y_i(j)-y_k(j))\cdot(rand-0.5)\cdot 2 \quad (2)$$

where rand represents a random value between 0 and 1. Calculate the new fitness value of the updated parameters by formula (1) and choose the one that possesses a higher fitness as the new employed bee.

Step 6. Send the onlooker bees onto the food sources. The onlooker bees apply the roulette selection method to choose the bee individual as the leading bee. Each onlooker continues to search new solutions just around the leading bee's solution space similar with Step 5, and calculate their fitness values. If the new solution is better than the original one, update the position of the employed bee which has been chosen.

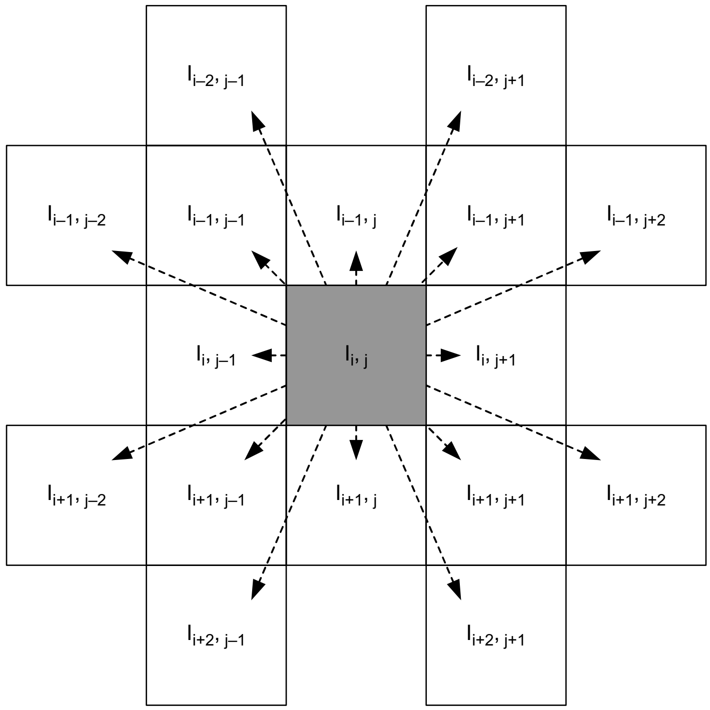
The roulette selection method means that the leading bee is chosen with the probability value. Probability values are calculated by using fitness values and the maximum fitness value. The formula is:

$$prob(i)=a*fitness(i)/\max(fitness)+b \quad (3)$$

Step 7. Stop the exploitation process of the sources and send the scouts into the search area. If the search times trial is larger than certain threshold limit, the employed bee gives up the solution. Then send the scout to search new food source.

Step 8. Store the food sources and their fitness values.

Figure 3 Clique for computing the fitness of pixel (*i*, *j*)



Section 2

Step 9. Search the similar food sources to form the edge of image. The food sources found in the above steps of Section 1 represent the scattered points of the edge. The edge can be formed by searching the similar food sources in a square of 3*3. The similar value is calculated by:

$$|f - f_r| \leq Th_1 \ \ and \ \ |f| \geq Th_2 \tag{4}$$

where f represents the fitness value of the new food source, and *fr* represents the fitness value of the food source found in the above steps. The threshold *Th1* and *Th2* can be set according to different images. Store all the similar food sources.

Step 10. Mark the food sources in Steps 8 and 9 in the image.

Our improved ABC algorithm is an effective expand of the original ABC, which is attributed to design the appropriate strategy for edge detection. In Section 1, the scattered points of the edge are found and stored. However, the edge of object is the connection of points. The steps in Section 2 are used to expand the edge so that more information of edge can be got.

Combination of visual attention and ABC algorithm

The detailed procedure of combination of visual attention and ABC algorithm for biological edge detection is shown in Figure 4.

As a combination of visual attention and improved ABC algorithm, our proposed edge detection method for UCAV is a optimized point searching scheme on salient map. Through several operations of visual attention model, salient regions which contain targets are extracted to accelerate the whole process and reduce the effect of noise interference.

Simulation results

To verify the feasibility and effectiveness of the proposed biological approach in this work, series of experiments are conducted. The parameters are set as: $Ns = 1{,}000$, $Ne = 500$, $Limit = 100$, $Iteration = 500$. The experimental results with the improved ABC algorithm for edge detection are shown in Figure 5.

In the first example (Figures 5 and 6), the target is the red ketch. The results show that the improved ABC algorithm for edge detection is feasible and effective. This method can obtain the edge information of the objects in the image and remove large environmental information and noise.

Then, the experiments are conducted using the proposed combination method of visual attention and ABC algorithm. Some results (Figure 7) clearly show that this combination method can successfully obtain the important part of the image and objects. It is feasible for object detection. Even though this method will make some information lost and we may not get the complete edge of object, it is enough for the target recognition.

To further prove the performance of the proposed biological method, we change the original image and conduct the experiment. In experimental results (Figures 8 and 9) of the combination method, the original image is not clear and includes some noise. From the results, we can know that this method can also successfully obtain the objects.

Conclusion

In this paper, the hybrid biological model of saliency-based visual attention and ABC algorithm is established for edge

Figure 4 The procedure of the combinational method

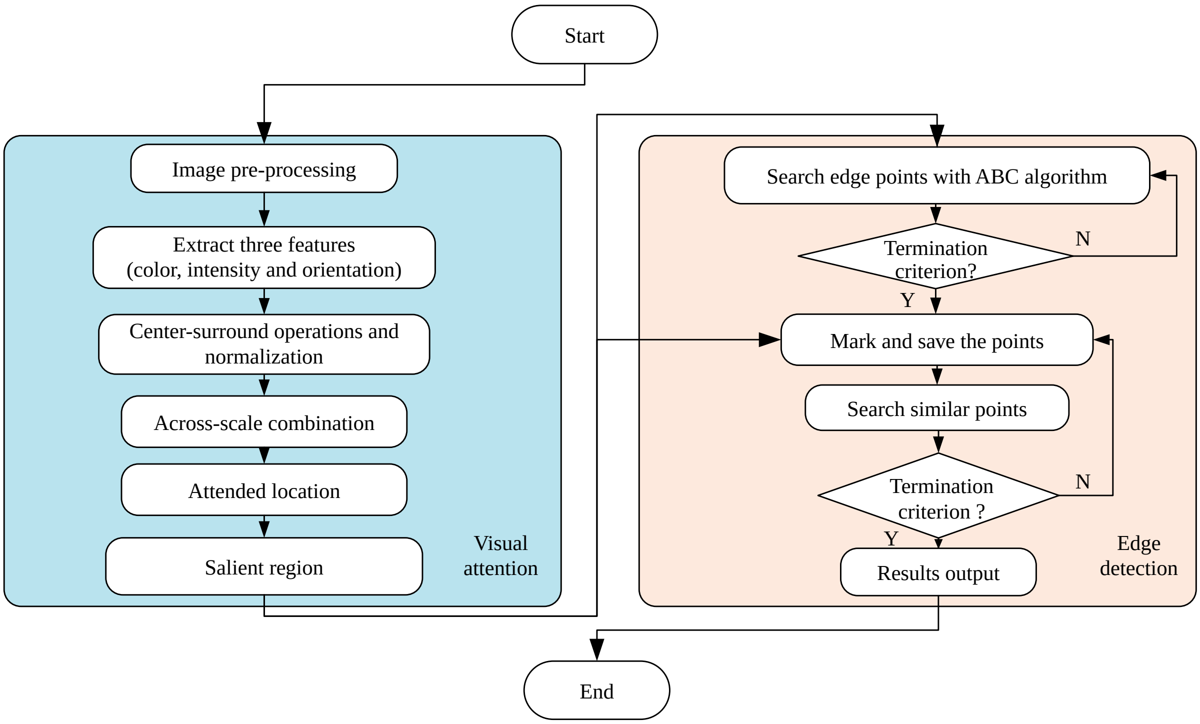
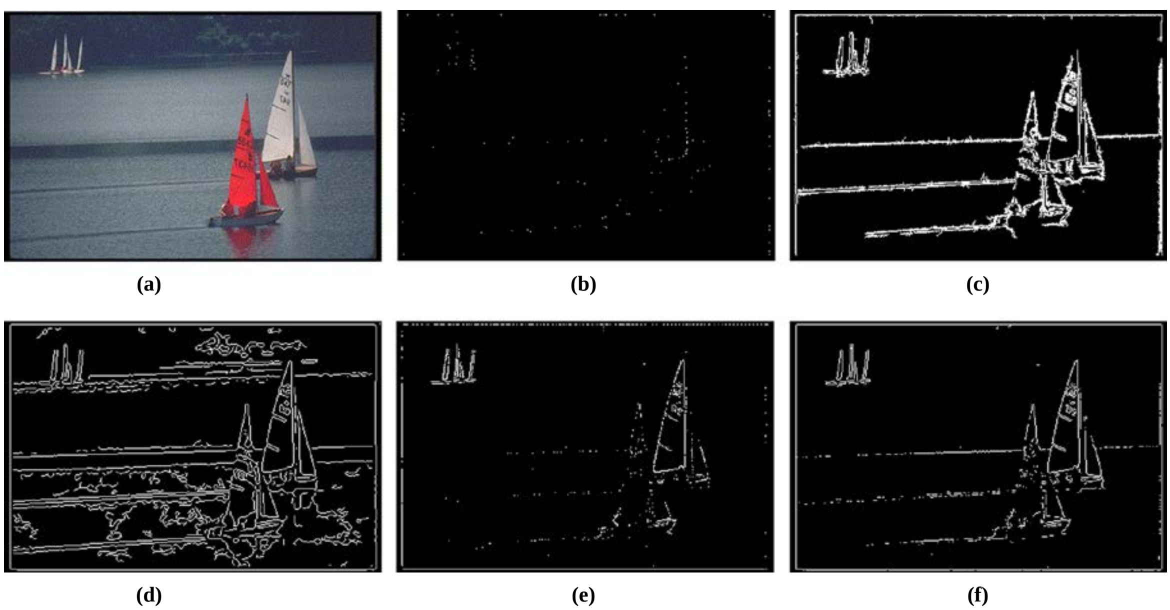


Figure 5 Original image and results of edge detection algorithms



Notes: (a) Original image; (b) and (c) are results of Sections 1 and 2 of our improved ABC algorithm; (d) Canny operator; (e) Roberts operator; (f) Sobel operator

detection of UCAV. The visual attention model can help find the target region fast and accurately, which can reduce the amount of information and make the following processes easier and simpler. The improved ABC algorithm can detect the target edge effectively and avoid the effects of environment and noise. The experimental results show that our proposed method is a feasible and effective way in target edge detection.

Our future work will focus on how to apply the proposed biological approach to solve other real-world problems, such as unmanned aerial vehicle (UAV), mobile robots, industry production line, and intelligent transportation.

Figure 6 Evolution curves of our algorithm

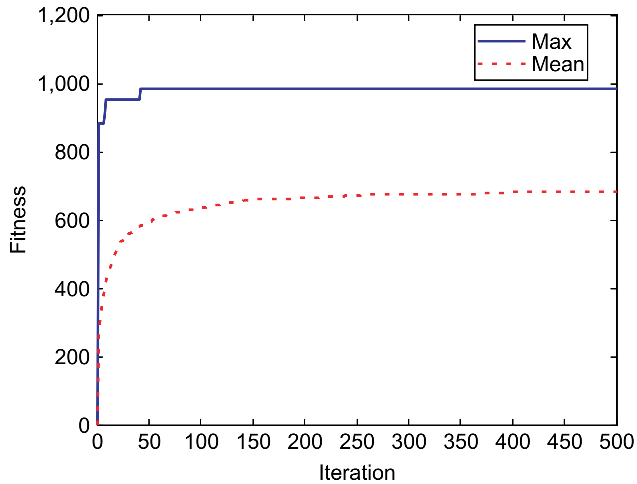
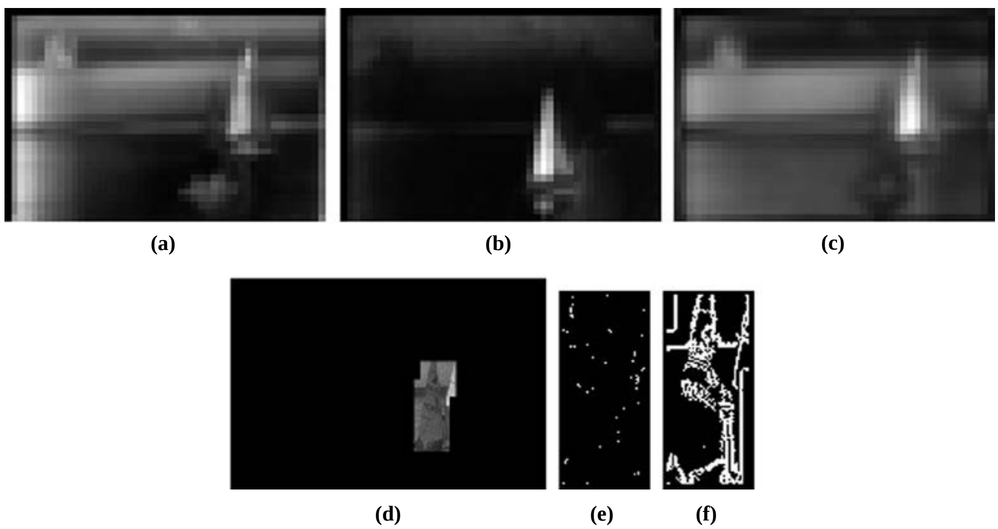
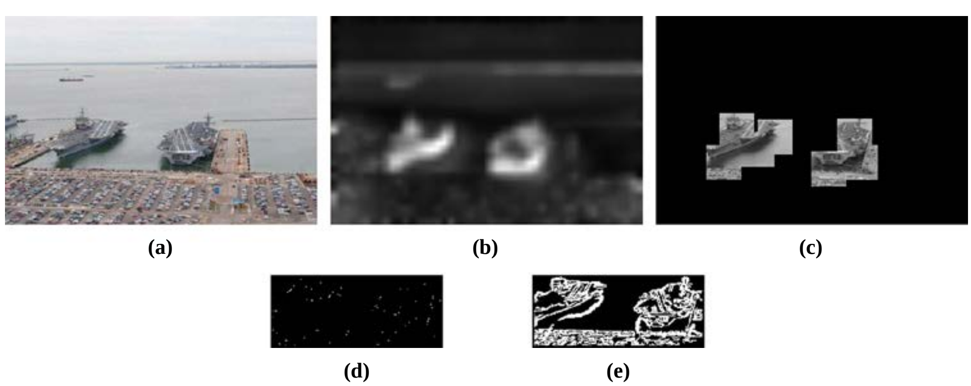


Figure 7 The processing results of edge detection with the model for the same original image



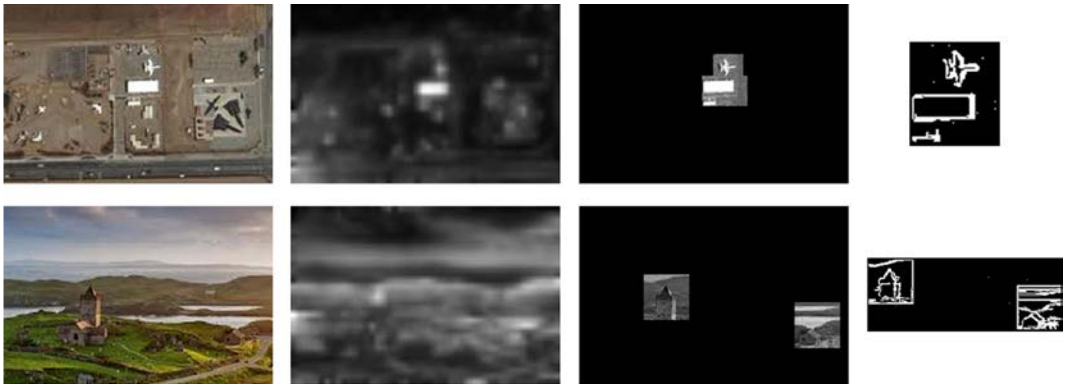
Notes: (a)-(c) Are three conspicuity maps: intensity, colour and orientation, respectively; (d) salient region; (e) points from Section 1 of the improved ABC algorithm; (f) edge of our method

Figure 8 Original image and results of edge detection algorithms



Notes: (a) Original image; (b) salient map; (c) salient region; (d) points from Section 1 of the improved ABC algorithm; (e) edge of our method

Figure 9 Results of edge detection algorithms for UCAV in different scenes



Notes: From left to right: original image, salient map, salient region and edge of our method

References

Bertuccelli, L.F. and Cummings, M.L. (2012), "Operator choice modeling for collaborative UAV visual search tasks", *IEEE Transcations on System, Man, and Cybernetics – Part A: Systems and Humans*, Vol. 42 No. 5, pp. 1088-1099.

Duan, H.B., Xu, C.F. and Xing, Z.H. (2010a), "Artificial bee colony optimization based quantum evolutionary for continuous optimization problems", *International Journal of Neural Systems*, Vol. 20 No. 1, pp. 39-50.

Duan, H.B., Zhang, Y.P. and Liu, S.Q. (2011), "Multiple UAVs/UGVs heterogeneous coordinated technique based on receding horizon control (RHC) and velocity vector control", *Science China Technological Sciences*, Vol. 54 No. 4, pp. 869-876.

Duan, H.B., Shao, S., Su, B.W. and Zhang, L. (2010b), "New development thoughts on the bio-inspired intelligence based control for unmanned combat aerial vehicle", *Science China Technological Sciences*, Vol. 53 No. 8, pp. 2025-2031.

Itti, L., Gold, C. and Koch, C. (2001), "Visual attention and target detection in cluttered natural scenes", *Optical Engineering*, Vol. 40 No. 9, pp. 1784-1793.

Itti, L., Koch, C. and Niebur, E. (1998), "A model of saliency-based visual attention for rapid scene analysis", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 20 No. 11, pp. 1254-1259.

Karaboga, D. (2005), "An idea based on honey bee swarm for numerical optimization", Technical Report TR06, Erciyes University Press, Kayseri, pp. 1-9.

Karaboga, D. and Akay, B. (2009), "A comparative study of artificial bee colony algorithm", *Applied Mathematics and Computation*, Vol. 214 No. 1, pp. 108-132.

Karaboga, D. and Basturk, B. (2007), "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm", *Journal of Global Optimization*, Vol. 39 No. 3, pp. 149-171.

Karaboga, D. and Basturk, B. (2008), "On the performance of artificial bee colony (ABC) algorithm", *Applied Soft Computing*, Vol. 8 No. 1, pp. 687-697.

Li, Z.C., Qin, S.Y. and Itti, L. (2011), "Visual attention guided bit allocation in video compression", *Image and Vision Computing*, Vol. 29 No. 1, pp. 1-14.

Lin, F., Dong, X.X., Chen, B.M., Lum, K.Y. and Lee, T.H. (2012), "A robust real-time embedded vision system on an unmanned rotorcraft for ground target following", *IEEE Transactions on Industrial Electronics*, Vol. 59 No. 2, pp. 1038-1049.

Liu, H.F., Chen, S.F., Zhang, Y. and Chen, J. (2012), "Modelling radar tracking features and low observability motion planning for UCAV", *IEEE Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Nanchang, China*, pp. 162-166.

Min, J.H., Kim, J.H., Jung, Y.K. and Kweon, I.S. (2012), "Visual lock-on to invisible target for unmanned aerial vehicle", *Electronics Letters*, Vol. 48 No. 14, pp. 835-837.

Parikh, N., Itti, L. and Weiland, J. (2010), "Saliency-based image processing for retinal prostheses", *Journal of Neural Engineering*, Vol. 7 No. 1, pp. 1741-2560.

Pradeep, S. (2002), "Nonlinear control of unmanned combat aircraft during take-off", AIAA Paper 2002-0250, paper presented at AIAA 40th Aerospace Sciences Meeting and Exhibit, Reno, NV.

Siagian, C. and Itti, L. (2007), "Rapid biologically-inspired scene classification using features shared with visual attention", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 29 No. 2, pp. 300-312.

Tian, J., Yu, W.Y. and Xie, S.L. (2008), "An ant colony optimization algorithm for image edge detection", *IEEE Congress on Evolutionary Computation (CEC), Hong Kong, China*, pp. 751-756.

Wise, K. (2003), "X-45 program overview and flight test status", AIAA Paper 2003-6645, paper presented at 2nd AIAA "Unmanned Unlimited" Conf. and Workshop and Exhibit, San Diego, CA.

Xu, C.F., Duan, H.B. and Liu, F. (2010), "Chaotic artificial bee colony approach to uninhabited combat air vehicle (UCAV) path planning", *Aerospace Science and Technology*, Vol. 14 No. 8, pp. 535-541.

Zhang, X.Y., Duan, H.B. and Yu, Y.X. (2010), "Receding horizon control for multi-UAVs close formation control based on differential evolution", *Science China Information Sciences* (*Science in China Series F*), Vol. 53 No. 2, pp. 223-235.

Zhao, Z.Y. and Lu, G.S. (2012), "Receding horizon control for cooperative search of multi-UAVs based on differential evolution", *International Journal of Intelligent Computing and Cybernetics*, Vol. 5 No. 1, pp. 145-158.

Further Reading

Xu, C.F. and Duan, H.B. (2010), "Artificial bee colony (ABC) optimized edge potential function (EPF) approach to target recognition for low-altitude aircraft", *Pattern Recognition Letters*, Vol. 31 No. 13, pp. 1759-1772.

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