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Shanjun Chen and Haibin Duan
Science and Technology on Aircraft Control Laboratory, Beijing University of Aeronautics and Astronautics, Beijing, China

Abstract
Purpose – The purpose of this paper is to propose an improved optimization method for image matching problem, which is based on multi-scale Gaussian mutation pigeon-inspired optimization (MGMPIO) algorithm, with the objective of accomplishing the complicated image matching quickly.
Design/methodology/approach – The hybrid model of multi-scale Gaussian mutation (MGM) mechanism and pigeon-inspired optimization (PIO) algorithm is established for image matching problem. The MGM mechanism is a nonlinear model, which can adjust the position of pigeons by mutation operation. In addition, the variable parameter (VP) mechanism is exploited to adjust the map and compass factor of the original PIO. Low-cost quadrotor, a type of electric multiple rotorcraft, is used as a carrier of binocular camera to obtain the images.
Findings – This work improved the PIO algorithm by modifying the search strategy and adding some limits, so that it can have better performance when applied to the image matching problem. Experimental results show that the proposed method demonstrates satisfying performance in convergence speed, robustness and stability.
Practical implications – The proposed MGMPIO algorithm can be easily applied to solve practical problems and accelerate convergence speed of the original PIO, and thus enhancing the speed of matching process, which will considerably increase the effectiveness of algorithm.
Originality/value – A hybrid model of the MGM mechanism and PIO algorithm is proposed for image matching problem. The VP mechanism and low-cost quadrotor is also utilized in image matching problem.

Keywords Quadrotor, Pigeon-inspired optimization (PIO), Image matching, Multi-scale Gaussian mutation (MGM), Unmanned aerial vehicles (UAVs), Variable parameter (VP)

Paper type Research paper

Introduction

Unmanned aerial vehicles (UAVs) are currently becoming increasingly popular in civilian and military fields, which have aroused great interests for its application. UAV is a type of very complex system which integrates different hardware and software components. The hardware components include global positioning system (GPS), camera, controller, inertial management unit (IMU), and the software components include image processing, path planning and inner loop control. UAVs with the ability to perform difficult tasks in hazardous environments have been used in various places. However, there are some defects for traditional UAVs such as high cost, low flexibility and large volume. Compared with traditional UAVs, the miniature UAVs like quadrotor has its own advantages in the field of computer vision, and it has been used widely. For example, quadrotor has been used in the China's variety show to shoot many times. Quadrotor was exploited to test six degrees of freedom flight (Yu and Ding, 2012). Low-cost quadrotor was used for autonomous visual tracking and landing (Bi and Duan, 2013). Based on considerations of cost and performance, we use the low-cost quadrotor assembled by ourselves as a carrier to carry binocular camera to obtain these images for image matching.

The development of image technology plays a very important role in the field of vision navigation, image processing and computer vision. For example, a binocular vision-based UAVs autonomous aerial refueling platform was established (Duan *et al.*, 2016). A new image processing method for discriminating internal layers was proposed (Lang *et al.*, 2014). The collapsed buildings were detected with the aerial images captured from UAV (Hua *et al.*, 2016), and vision navigation for aircrafts based on 3D reconstruction was utilized (Zhu *et al.*, 2015). While, image matching has always been a highlighted research topic in image processing, as it is a fundamental task for many applications of computer vision such as image registration and image fusion (Koutaki *et al.*, 2013). Image matching has also been widely applied in the fields of pattern recognition, three-dimensional reconstruction and motion analysis (Brown, 1992; Candocia and Adjouadi, 1997). As the importance of the image matching, many evolutionary algorithms (EAs) and improved methods,

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including artificial bee colony (ABC) (Karaboga and Basturk, 2007), genetic algorithm (GA) (Im *et al.*, 2002), particle swarm optimization (PSO) (Riccardo *et al.*, 2007) and ant colony optimization (ACO) (Duan, 2005), are proposed to achieve a better matching effect. Cauchy biogeography-based optimization based on lateral inhibition was used to solve the image matching problem (Wang and Duan, 2013). Duan and Yu utilized predator-prey PSO to achieve parameter identification of UCAV flight control system (Duan *et al.*, 2013). In general, almost all kinds of image matching algorithms which have been proposed (Duan, 2005; Karaboga and Basturk, 2007; Riccardo *et al.*, 2007; Zhang and Chen, 2008; Elboher and Werman, 2013; Duan *et al.*, 2013; Koutaki *et al.*, 2013; Wang and Duan, 2013) can be divided into the algorithm based on image statistics and the algorithm based on image characteristics (Ma *et al.*, 2009). The algorithm based on image statistics analyzes the attributes of an image to measure the similar degree between the template image and the reference image under test which is also called the original image. Its measurement methods mainly include the minimum distance measurement, correlation function and probability measure. One of the most commonly used methods is the minimum distance measurement, including square difference, mean square difference, absolute difference and absolute difference. The algorithm-based image characteristics make use of some image features such as spatial location, point features, image edge ,texture ,energy, shape and entropy to evaluate the similar degree of the two images. Because the performance of the algorithm based on image characteristics is associated with the choice of image features, it varies when choosing different image features, which leads to this type of algorithm with a weak robustness. The algorithm based on image statistics is independent from the extensive characteristics extractions. Therefore, it is widely used and shows a better performance.

Image matching is a process of searching the template image in the reference image under test by using a specific algorithm. In general, the image under test is larger than the template image. As the different of perspectives and filming equipment, the same object is different in different time of imaging. In addition, the difference between the template image and the image under test is expanded as the influence of noise, rotating, interference and image pre-processing, which increases the difficulty to matching. At present, during the process of image matching, the matching precision, matching speed, versatility and robustness are the main evaluation standards. To improve these standards, many algorithms have been exploited. Although the application of these algorithms has been made great development in many ways, there are still many aspects such as computing time, stability, and robustness having room for improvement. In this paper, multi-scale Gaussian mutation pigeon-inspired optimization (MGMPIO) is utilized for image matching problem, which combines the advantages of a nonlinear model.

The original pigeon-inspired optimization (PIO) algorithm is a new swarm intelligence optimization algorithm, which was firstly proposed by Duan and Qiao (2014), and inspired by the features of the homing pigeons. Here, we are ready to utilize the PIO algorithm to solve the problem of image matching. In this type of algorithm, two kinds of operators, including the map and compass operator model based on magnetic field and sun and the landmark operator based on landmarks, are used to search the optimal solution. In early iterations, the speed of the pigeon mainly depends on its previous speed inertia according to the map and compass operator. Thus, the global search ability of PIO is strong because the speed of the pigeons is randomly given. This operator contributes to the diversity of population and enables the algorithm to have better stability. While in late iterations, every pigeon is flying straight toward the center of all pigeons according to the landmark operator. This operator contributes to the convergence rate of the algorithm. The PIO algorithm has been proven to converge more quickly and more stable comparing with the standard DE algorithm, and with the increasing of pigeon number, the convergence performance is much better (Duan and Qiao, 2014). However, the basic PIO algorithm falls into local optimum easily while keeping a higher convergence speed. To improve the performance of the basic PIO algorithm, improved mechanism has been investigated such as Li and Duan (2014) used the improved PIO algorithm to accomplish the target detection task for UAVs. In our work, some improved mechanism is also exploited in the basic PIO algorithm.

A nonlinear model can make the system become more flexible by setting the appropriate parameter. In addition, it can determine its own value according to the actual situation. The nonlinear model has been applied widely in recent years. For example, Huang and Ma investigated the nonlinear attitude-orbit coupling dynamics and control for the reconfiguration of a two-satellite coulomb tether formation near earth-moon libration points (Huang *et al.*, 2014). Jeon and Eun, (2014) exploited nonlinear multiple models to study distributed estimation fusion problem. In this work, the nonlinear models, including the multi-scale Gaussian mutation (MGM) mechanism (Morgan and Druckmüller, 2014) and variable parameter (VP) mechanism (Chatterjee and Siarry, 2004), are proposed to improve the performance of the basic PIO algorithm for image matching problem and the improved PIO algorithm is called MGMPIO. Through adjusting the change of the previous speed inertia part, the VP mechanism makes the PIO algorithm has stronger global searching ability at early iterations and stronger local searching ability at later iterations (Riccardo *et al.*, 2007). In that case, the precision and convergence rate of the original PIO algorithm can be improved. The introduction of MGM mechanism makes some pigeons get rid of the restriction of the basic PIO algorithm's update rule (Tao and Xun, 2009), which can improve the ability to get rid of local optimum easily.

The remainder of this paper is organized as follows. Section 2 introduces the low-cost quadrotor. Then, the original PIO algorithm is given in Section3. Section 4 describes the MGMPIO algorithm in detail, including the MGM mechanism and VP mechanism. A series of experiments are conducted to verify the performance of the MGMPIO algorithm in Section 5. The concluding remarks are contained in the final section.

Low-cost quadrotor

Quadrotor is an electric multiple rotorcraft containing four rotors, and there are two pairs of counter-rotating, fixed-pitch blades located in the four corners of its body. As early as 1920s, the idea of using four rotors is realized as a full-scale helicopter (http://en.wikipedia.org/wiki/Quadrotor). In recent years, with the development of computer vision, and new materials and new micro-electro mechanical continually spring up, quadrotor gets rapid development and wide application. There are several advantages in comparison to traditional helicopters, including novel appearance, simple structure, low cost and excellent performance in a unique way of flight control (Tian and Xun, 2008). In addition, by using four rotors, each individual rotor can have a smaller diameter. In that case, the damage caused by the rotors can be reduced greatly. Furthermore, quadrotor can finish a variety of flight attitude such as vertical take-off and landing, free hovering. At the same time, four rotors can produce greater lift, which ensure that the fuselage can carry a binocular camera. In view of the above advantages of quadrotor, we utilize a low-cost quadrotor with a binocular camera to obtain the images needed by image matching. As a low-cost quadrotor, in addition to its own advantage of low cost, we assembled the quadrotor by using the selected module where the APM flight control system is used. The APM flight control system is a kind of open-source system with the main chip ATMEGAL 1280/2560, which supports for three axes, four axes, six axes, fixed wing and helicopter. Meanwhile, this kind of system exploited two-stage PID control method. The first level is navigation grade, and the second is to control level. In this way, the cost will be further compressed. The quadrotor we assembled is shown in Figure 1(a), which is a Wi-Fi-controlled quadrotor which is capable of carrying a binocular camera. Height is 300mm and diameter is 650mm. The APM flight control system as a platform offers an open application programming interface (API) and freely downloadable software development kit (SDK) for developers (Krajnik *et al.*, 2011). Many useful pieces of development information can be found on the developers' websites or the official forum. The binocular camera is shown in Figure 1(b), which is a kind of MERCURY series CCD/CMOS industrial camera.

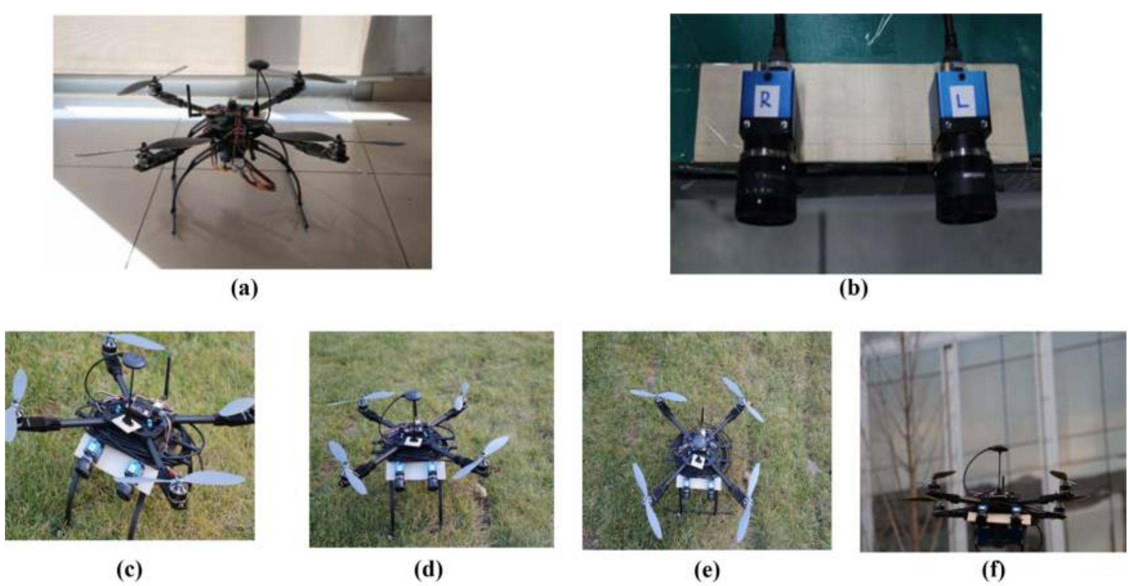
Pigeon-inspired optimization algorithm

According to Duan's theory (Duan and Qiao, 2014) in solving air robot path planning problem, the PIO algorithm can be described as follows:

Firstly, initialize the parameters. The maximum number of iterations for the map and compass operator is T_1, and T_2 is for the landmark operator. The number of pigeons is set to N. Every pigeon's position and velocity are randomly initialized within the search space. The position and velocity of the i^{th} pigeon is donated as $X_i(t) = [x_{i1}, x_{i2}, \ldots\ldots, x_{iD}]$ and $V_i = [v_{i1}, v_{i2}, \ldots\ldots, v_{iD}]$, where D represents the dimension of the search space. Then, choose the best position by calculating the quality of all the pigeons.

In the PIO model, according to the characteristics of the homing pigeons, two operators, including the map and compass operator and the landmark operator, are utilized. At early iterations, as the scope of optimal position is not confirmed and pigeons are far away from the destination, the map and compass operator is used, which is based on the magnetic field and sun. In the map and compass operator, the velocity of each pigeon is determined by their own current velocity and position, as well as the global optimal position information, which can be depicted by equation (1). Then the position of each pigeon at next generation is determined by equation (2) (Duan and Qiao, 2014). The pigeons are manipulated by the following equations (1) and (2):

Figure 1 Quadrotor picture from different views



Notes: (a) Quadrotor; (b) binocular camera; (c) side view; (d) front view; (e) top view; (f) vertical view

$$V_i(t) = V_i(t-1) \cdot e^{-Rt} + rand \cdot (X_g - X_i(t-1)) \quad (1)$$

$$X_i(t) = X_i(t-1) + V_i(t) \quad (2)$$

where R represents the map and compass factor which can control the changing trend of pigeon's own speed inertia as the iteration goes. *rand* is a random number within [0, 1], X_g represents the current global best position, which can be obtained by comparing all the positions among all the pigeons.

After a certain number of iterations, the pigeons fly close to their destination and will rely on landmarks neighboring them. The landmark operator instead of the map and compass operator is exploited to search the best position. In the landmark operator, every pigeon can fly straight to the destination which is the center of all pigeons, and the number of pigeons decreases to half of the last generation. Half of all the pigeons that are far from the destination and unfamiliar to the landmarks will follow the pigeons who are familiar to the landmarks. In that case, it is possible for two pigeons at the same position, and the destination will be found by the pigeons that are close to their destination quickly. In Duan's model (Duan and Qiao, 2014), the center of all pigeons is their destination in the t^{th} iteration, which can be written as:

$$X_c = \frac{\sum X_i(t) \cdot fitness(X_i(t))}{N_p \cdot \sum fitnesss(X_i(t))} \quad (3)$$

where *fitness*() is the function to evaluate the quality of the pigeon individually, N_p represents the number of pigeons in the t^{th} iteration, which is the half of last iteration amount. The position of each pigeon is updated by the following equation:

$$X_i(t) = X_i(t-1) + rand \cdot (X_c(t) - X_i(t-1)) \quad (4)$$

The PIO algorithm has been proven to be effective and feasible when it is exploited to solve air robot path planning problem. But it is easy to get into the local optimum sometimes; thus, it is essential improve the robustness and stability of the basic PIO algorithm.

Model development

Variable parameter mechanism

In the basic PIO algorithm, according to equation (2), we can see that the next iteration position of pigeon decided jointly by the current speed and position of pigeon's own, and the speed direction and size of current pigeon determine the change of pigeon's direction and size of next generation. We can also know that the current speed relies on previous speed inertia and global optimal position X_g by equation (1). We hope that the PIO algorithm has larger global search ability at early iterations, so that we can quickly narrow the range of the searching space for the optimal value to improve the convergence speed of algorithm, and in later iterations with stronger local development ability (Tian and Xun, 2008). In the original PIO, there is a formula e^{-Rt} in the previous speed inertia part which represents $V_i(t-1) \cdot e^{-Rt}$. The value of the formula e^{-Rt} decreases gradually with the increase of the number of iterations, so that at early iterations, the previous speed inertia part takes a heavy weight in determining the current velocity, and the effect of the global optimal position X_g part, which represents $rand \cdot (X_g - X_i(t-1))$, is relatively light. Therefore, the current speed of pigeons mainly depends on the previous speed inertia part (Chatterjee and Siarry, 2004). Because the previous speed inertia part represents the pigeons' own information, different pigeon has different information, which has strong subjectivity and uncertainty. In that case, at early iterations, pigeons can locate any location of search space, and the PIO algorithm shows great global searching ability. On the contrary, in the late of iterations, the previous speed inertia part has become small. The current speed of pigeons mainly depends on the global optimal position X_g part (Duan and Qiao, 2014). As the global optimal position X_g part represents the global shared information, it has the characteristics of prompting aggregation and convergence. In that case, it can accelerate the convergence speed of the original PIO algorithm. However, through analysis, we find that once R is established, the value of formula e^{-Rt} has normally a fast reduced trend as the increase of the number of iterations. There is a high chance that the value of formula e^{-Rt} has become very small in the case of having not found the range of the global optimal position for the original PIO algorithm, which leads to the loss of strong global search ability. Therefore, it will be easy for the original PIO algorithm trapped in local optimal position and cannot find the global optimal position finally.

Based on the above shortcomings, here imitating the thought of inertia weight (Shi and Eberhart, 1998), we adjust R by utilizing the VP mechanism to control the change of the previous speed inertia part on the basis of the PIO algorithm. This new algorithm is called R-adjustable PIO (RPIO) algorithm. The improved previous speed inertia part has a slow attenuation trend at early iterations, so that it has a stronger global search ability to enhance the probability of finding the range of global optimal position accurately. In the later of iterations, the improved previous speed inertia part has a rapid attenuation trend, so that it can find the global optimal position quickly on the basis of finding the range of the global optimal position, speeding up the convergence speed of the basic PIO algorithm. The specific improvement is as follows:

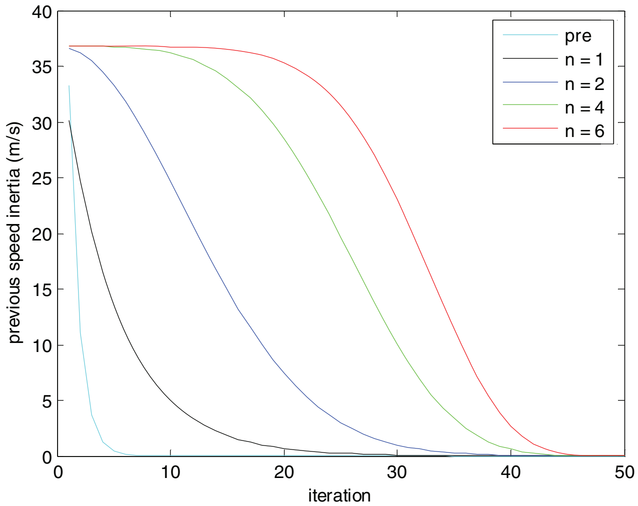
The VP mechanism is designed as (5). The speed of each pigeon is updated by equation (6), where t represents the current generation, T_1 represents the largest number of iterations for the map and compass operator and n represents a parameter, which can set freely by us (Chatterjee and Siarry, 2004).

$$R = R_{\min} + (R_{\max} - R_{\min}) \cdot \left(\frac{t}{T1}\right)^n \quad (5)$$

$$V_i(t) = V_i(t-1) \cdot e^{(-R)} + rand \cdot (X_g - X_i(t-1)) \quad (6)$$

Here, a series of comparative experiments are conducted when $n = 1$, $n = 2$, $n = 3$, $n = 6$ and the original version that has not been improved for the previous speed inertia part to test effect. The comparative results for the speed of the previous inertial part are presented in Figure 2, where the X-axis denotes the number of iterations and has no units, and the Y-axis represents the previous speed inertia ($V_i(t-1) \cdot e^{-Rt}$) in equation (1) and its unit is m/s.

Figure 2 The changing trend of pigeon's own previous speed inertia for different situations



In Figure 2 represents the changing trend curves of no processing previous speed inertia part. The parameters are set as: $V_i(t-1) = 100$, $R_{max} = 11$, $R_{min} = 1$, T1 = 50, and the no processing parameter R is set to 1.1. From Figure 2, we can see that the changing trend of the previous speed inertial part has a distinct improvement. At early iterations, the decline curves show that the previous speed inertia part that not be improved has a fast reducing trend, and rapidly decay trends to 0. But the improved previous speed inertia part has a slow attenuation trend. Especially when $n = 6$, it almost did not reduce in early iterations. At the same time, in the late of iterations, the improved previous speed inertia part reduced quickly. In that case, The RPIO algorithm not only can ensure larger global search ability, but also has stronger local search ability.

Multi-scale Gaussian mutation mechanism

Through the improvement of the above VP mechanism, the RPIO algorithm has a good performance in comparison with the original PIO algorithm. By many times test, we find that the large R value is conductive to the improvement of the convergence speed. To ensure a faster convergence speed, we can increase the value of R_{max} and R_{min}. But it will speed up the declining trend of the previous speed inertial part. From equation (6), we can see that the closer to the current global best position X_g, the velocity is smaller. Therefore, during the process of chasing the best position, the PIO algorithm shows a stronger convergence as the iteration goes. Especially in the late of iterations, it will become particularly evident. If the region of the best position has not been found at early iterations, as the increase of the R value, it will be easier to fall into local optimal position and eventually cannot find the global optimal position. In view of above analysis, if the speed or position of pigeons makes variation (Morgan and Druckmüller, 2014), the pigeons can get rid of the restrictions of the PIO algorithm's update rule to achieve the search of the other space, jumping out of the local optimal position and further improving the probability to find the global optimal position. Through systematic analysis and comparison, here we use the MGM mechanism (Li *et al.*, 2004) to make a further improvement for the RPIO algorithm. This new improved algorithm is called MGMPIO. The Gaussian distribution is also called the normal distribution, which is decided by the standard deviation σ and the mean μ of two parameters. Obey one-dimensional Gaussian distribution denoted as $N(\mu, \sigma)$. Its density function $f(x)$ is defined as equation (7):

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} \cdot e^{\frac{(x-\mu)^2}{2\cdot\sigma^2}} \tag{7}$$

Gaussian mutation is a process that any dimension of pigeon's position makes variation according to a certain probability P (Morgan and Druckmüller, 2014). Formula is as equation (8), where i represents the i^{th} pigeon, j represents the j^{th} dimension:

$$X_{ij} = X_{ij} + N(\mu, \sigma) \tag{8}$$

According to the Gaussian distribution's theory, the size of the standard deviation determines the distance of mutated pigeon away from the original position. The greater standard deviation, the probability of the mutated pigeon far away from the original position is bigger. The smaller standard deviation, the pigeon will remain in its own original position with a large probability. If we determine the size of the standard deviation σ according to the size of the position's fitness of pigeon (Li *et al.*, 2004), the pigeon that has a smaller fitness gets a bigger standard deviation σ, which can make it has a greater probability to locate other locations of the search space to search, and the pigeon that has a greater fitness gets a smaller standard deviation σ, which can make a further search to all around the current position. In that case, the MGMPIO algorithm not only can enhance the probability of jumping out of local optimal position, but also accelerate the convergence speed of the algorithm. The specific design is as equation (9):

$$\sigma = L \cdot \left(1 - \frac{fitness(P_{now})}{fitness(P_{final})}\right) \cdot (X_{ij}\max - X_{ij}\min) \tag{9}$$

where L represents a parameter which depends on the specific situation, *fitness*() represents the objective function which describes the similarity of the image under test and the template, $fitness(P_{now})$ represents the similarity value of the current pigeon position, $fitness(P_{final})$ represents the similarity value of the global optimal expected position and $[X_{ij}\min, X_{ij}\max]$ represents the search interval of the j dimension.

On the basis of the above improvements, if we also adopt MGM mutation to the current global optimal position X_g after each iteration, we can change the update of the pigeons velocity at the next iteration by changing the X_g, which can make pigeons locate other parts of the searching space to search, so as to further increase the probability of finding the global optimal position. But the MGM mechanism cannot be added randomly; it should satisfy some conditions. Here, we introduce the notion of the degree of pigeon's focus (Li *et al.*, 2004); its function $D(X_i, X_g)$ is defined as equation (10).

$$D(X_i, X_j) = \max_{i=1,2,\ldots,N} \sqrt{\sum_{j=1}^{D} (X_{gj} - X_{ij})^2} \tag{10}$$

As the $D(X_i, X_g)$ value will get smaller as the iteration goes, we established bounds A (Karaboga and Basturk, 2007). When $D(X_i, X_g)$ is smaller than the value of the A, it indicates that the pigeons gather closely, which will make the algorithm have a weak ability to search in the global search space. In that case, the MGMPIO algorithm will show a strong convergence as the iteration goes and falls into local optimal position easily. Same as above, here we determine the size of the standard deviation σ according to the size of the global optimal position's fitness of the t^{th} iteration and use the MGM mechanism again. The specific design is as equations (11) and (12).

$$\sigma = L \cdot \left(1 - \frac{fitness(X_g)}{fitness(P_{final})}\right) \cdot (X_{ij}\max - X_{ij}\min) \tag{11}$$

$$X_{gj} = X_{gj} + N(\mu, \sigma) \tag{12}$$

where j represents the j dimension likewise. Through the above improvements, the MGMPIO algorithm further contributes to the jumping out of the local optima.

Implementation procedure

The implementation procedure of our MGMPIO can be described as follows:

- *Step 1*: Image pre-processing. Obtain the original image and the template image. Then, convert them into gray-scale format.
- *Step 2*: Initialize parameters. Initialize the parameters of the MGMPIO algorithm such as the number of pigeons N, the value of bounds A, the search space dimension D, the value range of the factor for the map and compass operator $[R_{min}, R_{max}]$ and the maximum number of iteration T_1 and T_2 for two operators.
- *Step 3*: Initialize the velocity and position of each pigeon randomly within the scope of the allowed. Compare each pigeon and calculate the fitness value, finding out the optimal pigeon to initialize the global optimal fitness value and optimal position.
- *Step 4*: Operate map and compass operator. Utilize equation (5) to update the factor R firstly.
- *Step 5*: Update pigeons. Update the velocity and position of every pigeon by using equations (2) and (6) and calculate the fitness of the newly generated pigeons.
- *Step 6*: Add MGM. Compare with the established probability P, if a random value between 0 and 1 is smaller. Then add MGM to the newly generated pigeons' position according to equations (8) and (9).
- *Step 7*: Compare the fitness of pigeons before and after mutation. If the fitness added by the MGM is better, replace the position of pigeons before mutation with the better pigeons' position. Otherwise, remain the same as before.
- *Step 8*: If N newly generated pigeons have been generated, go to Step 9. Otherwise, go to Step 5.
- *Step 9*: Update the global optimal position X_g and optimal fitness. Calculate and compare all the newly generated pigeons' fitness and find the new best position.
- Step 10: Calculate the degree of pigeon's focus $D(X_i, X_g)$ according to equation (10).
- *Step 11*: Add MGM. Compare with the established bounds A, if the value of the formula $D(X_i, X_g)$ is smaller. Then, add MGM to the global optimal position X_g according to equations (11) and (12).
- *Step 12*: Calculate and compare the fitness of the newly generated X_g before and after mutation, if the fitness added by the MGM is better, then replace the pigeons' global optimal position before mutation with the better global optimal position. Otherwise, remain the same as before.
- *Step 13*: If the number of iterations is more than T_1, go to Step 14. Otherwise, go to Step 4.
- *Step 14*: Operate the landmark operator. Rank all pigeons according their fitness values and update the number of pigeons where half of the pigeons whose fitness is low will be discarded.
- *Step 15*: Calculate the center position of all pigeons according to equation (3). This center position is the desirable destination, and all pigeons will fly to the destination by adjusting their flying direction according to equation (4).
- *Step 16*: Update the global optimal position X_g and optimal fitness.
- *Step 17*: If the current number of iteration t reaches to $T_1 + T_2$, stop the iteration and output the solution. Otherwise, go to Step 14.

The detailed flow chart of the improved MGMPIO approach for image matching is shown in Figure 3.

Theoretical analysis

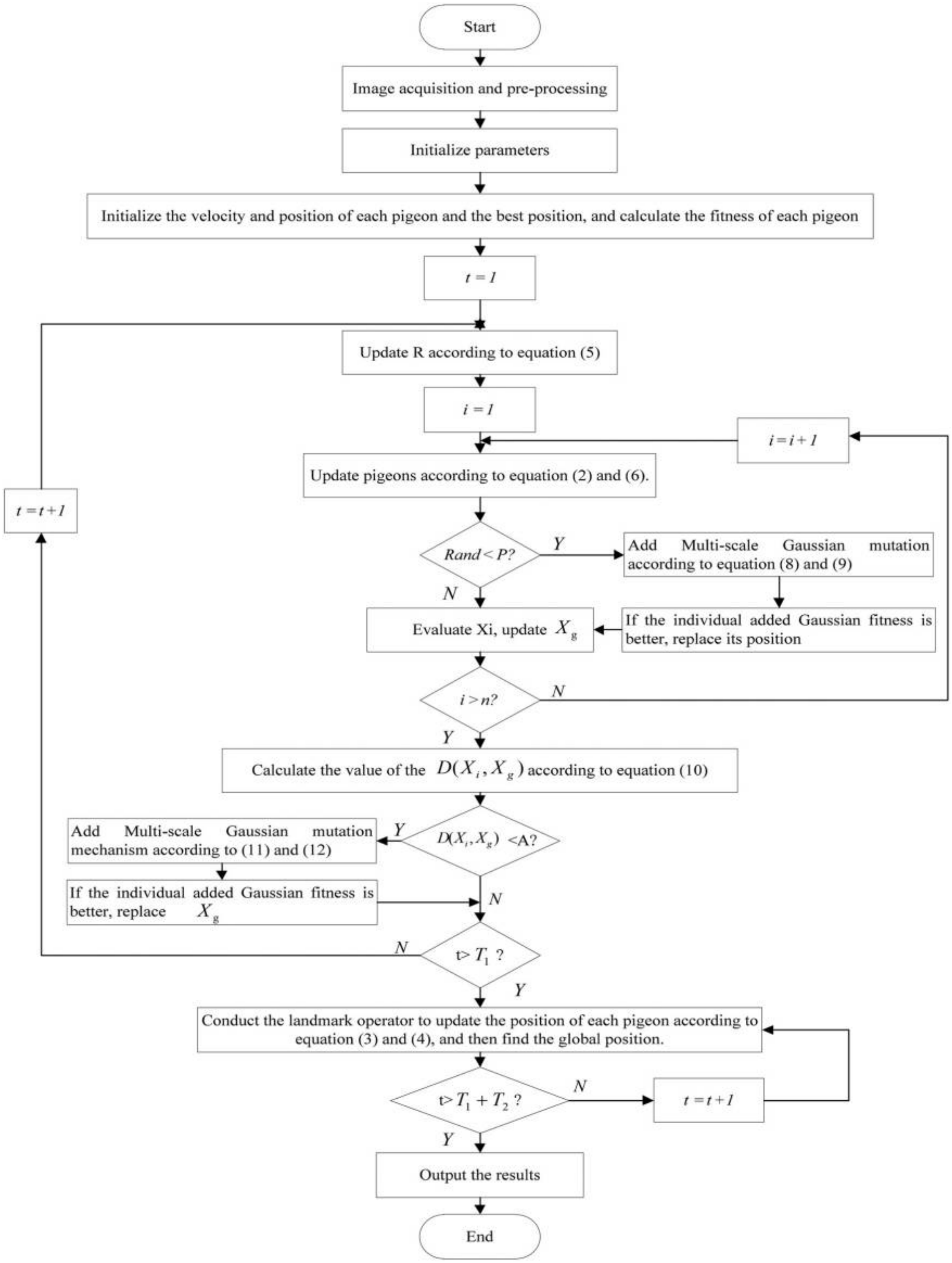
The theoretical analysis of evolutionary algorithms is very important. Here, we have concisely analyzed our MGMPIO algorithm in respect of global convergence property and computational complexity. In the original PIO algorithm, through the landmark operator, the algorithm is able to quickly converge to the optimum position in later iterations. In MGMPIO, the speed of pigeons adjusted by the VP mechanism can accelerate the rate of finding the region of the global optimal position; thus, there is faster convergence rate compared the original PIO. In addition, the MGM mechanism enables the algorithm to get rid of local optimal position, which is conductive to global convergence. So, the global convergence performance of MGMPIO is superior to the original PIO.

We analyzed the time complexity of each operation in the original PIO and that of these added operation in MGMPIO. And, the result is given in the Table I. Therefore, the total complexity of the added operations in MGMPIO in all iterations is $\Theta(2NT1)$. Although, these added operations implement more calculations on the original of PIO. It is worthy for the significant improvement of performance.

Comparative experimental results and analysis

To test the performance of our proposed MGMPIO, we chose three cases to carry out experiments. For Case 1, the original image is shown in Figure 4(a), and the template image is shown in Figure 4(b). The task is to find out two benches in

Figure 3 Detailed flow chart of the improved MGMPIO



the original image. In this paper, the parameters for MGMPIO are shown in Table II. All the pictures used for experiments originate from our assembled low-cost quadrotor and binocular camera introduced in Section 2, and all the following experiments are implemented on a PC with Intel Core i5, 2.6-GHz CPU, 4-GB memory and 64-bit Windows 7. All algorithms are implemented by MATLAB 8.0.0.783(R2012b).

The control parameters in the MGMPIO algorithms are chosen as follows: parameter P denotes the probability for Gaussian mutation, and its value depends on the specific situation. In general, for complex problems, mutation

Table I Parameters for MGMPIO

	Operation	Time complexity
Operation in original PIO	Parameters initialization	$\Theta(NT1)$
	Update each pigeon's position during the map and compass operator	$\Theta(NT1)$
	Update each pigeon's velocity during the map and compass operator	$\Theta(NT1)$
	Calculate the fitness of each pigeon during the map and compass operator	$\Theta(NT1)$
	Arrange all pigeons by ascend during the landmark operator	$\leq \Theta(2Nlog\,N(1-0.5^{T2}))$
	Calculate the center coordinates of all individuals	$\Theta(2N(1-0.5^{T2}))$
	Update each pigeon's position during the landmark operator	$\Theta(2N(1-0.5^{T2}))$
	Calculate the fitness of each pigeon during the landmark operator	$\Theta(2N(1-0.5^{T2}))$
Added operation in MGMPIO	Update the map and compass factor R in each iteration by equation (5)	$\Theta(T1)$
	Calculate the standard deviation σ by equation (11)	
	Pigeons' mutation operation by equation (12)	$\Theta(0.32NT1)$
	Calculate the degree of pigeon's focus by equation (10)	$\Theta(2NT1)$

operation is able to strengthen the ability of the algorithm to find the optimal solution, and it is essential to appropriately increase the probability of mutation operation. But in some simple questions, good results can be obtained by the standard algorithm. In this paper, we choose $p = 0.32$ is appropriate. Parameter A is as the reference for aggregation degree; it mainly depends on the number of pigeons. Its value can be roughly determined by the formula $\pi \cdot A^2 = 15N$ and the precise adjustment is then carried out. When the scope of the search space is large, a larger A is necessary. In this paper, we choose $A = 26$ is appropriate. Parameter L in equation (9) controls the range of the standard deviation, usually preferably from one to two times of the search space. In this paper, we choose $L = 2$. The large R value is conductive to the improvement of the convergence speed. To ensure a faster convergence speed, we can increase the value of R_{max} and R_{min}. But it will speed up the declining trend of the previous speed inertial part in equation (1). As the R value increases, it will be easier to fall into local optimal position and eventually cannot find the global optimal position. Through further analysis, we find that, in addition to the parameter n, the value of $(R_{max} - R_{min})$ also affects the changing trend of the previous speed inertial part. Thus, we can set up a large R_{max} value while a small R_{min} value is determined. Through a series of tests, we find that a good performance can be achieved when $R_{max} = 10$, $R_{min} = 0.1$, $n = 12$. Other parameters are selected empirically through trial and error.

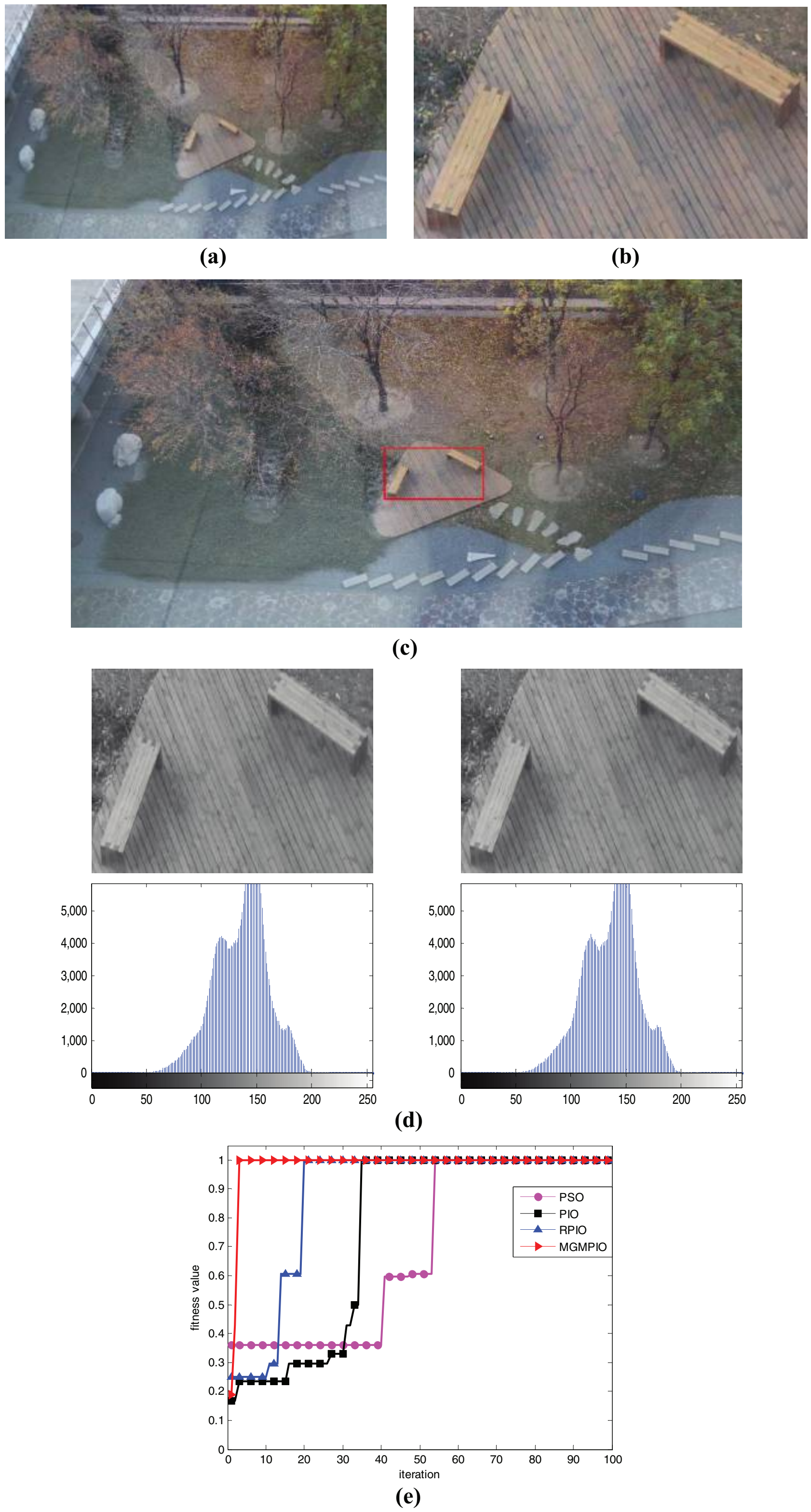
The matching result for Case 1 is shown in Figure 4(c). From Figure 4(c), it is obvious that the MGMPIO algorithm can accurately find the location of the template image in the original image, which indicates that the MGMPIO algorithm is feasible. To test the advantages of the MGMPIO algorithm relative to the original PIO algorithm, we conducted a set of contrast experiments. At the same time, we also choose the other algorithms, including PSO and RPIO, to further compare their performance. The result of contrast experiments is shown in Figure 4(e). It is evident from Figure 4(e) that the MGMPIO algorithm has the fastest convergence speed in all of these algorithms, which confirms that the MGMPIO algorithm has a better effectiveness. Here, we also show the histogram of image that has been matched successfully in the Figure 4(d). Its abscissa denotes gray scale, and its ordinate represents the number of pixels. The left of Figure 4(d) is template image histogram, and the right of Figure 4(d) is the histogram matched in original image.

Further experiments are given in Figure 5 to test the stability of the improved MGMPIO algorithm. Here, all the algorithms run for 10 times independently. The experimental results for PSO, PIO, RPIO and MGMPIO are shown in Figures 5(a)-(d) separately. Moreover, different algorithms are applied to the same Case 1, and they have the same fitness function. The number of pigeons and the maximum number of iterations for different algorithms are set to be same. From the results in Figure 5, it is clear that, compared with the original PIO algorithm, the evolutionary curves of the MGMPIO algorithm are more stable. Compared with other two algorithms, the MGMPIO algorithm also shows a better stability. In the experiment, we decrease the demand for speed to ensure the stability of the original PIO algorithm. If the original PIO algorithm has the same demand for speed as the MGMPIO algorithm, it cannot guarantee to match successfully in each time. When we just use the VP mechanism to improve the original PIO algorithm, the results in Figure 5(c) indicate that the RPIO algorithm can improve the convergence speed. But it is easy to fill into local optimal solution and cannot find the global optimal solution. After adding the MGM mechanism, from the results in Figure 5(d), it is obvious that the MGMPIO algorithm not only can improve convergence speed significantly, but also maintain good stability.

To further investigate the robustness of the MGMPIO algorithm, a series of experiments are conducted for the other two different cases. Figures 6 and 7 are the results for Case 2 and Case 3, respectively. Just like Case 1, Figure 6(a) and Figure 7(a) are original images. Figure 6(b) and Figure 7(b) are template images. Figure 6(d) and Figure 7(d) are histograms of images that have been matched successfully. Figure 6(e) and Figure 7(e) are the evolutionary curves with PSO, PIO, RPIO and MGMPIO. For Case 2, the task is to find out the car in the original image. The task for Case 3 is to find out the aircraft in the original image. Here, the parameters for Case 2 and Case 3 are the same as the Case 1.

From Figure 6(c) and Figure 7(c), it also shows that the location of the target template image is found accurately in the original image. The accuracy of our proposed MGMPIO

Figure 4 The experimental results of image matching for Case 1



Notes: (a) Original image for Case 1; (b) template image for Case 1; (c) results for image matching; (d) the histogram of image that has been matched successfully and template; (e) evolutionary curves with PSO, PIO, RPIO and MGMPIO

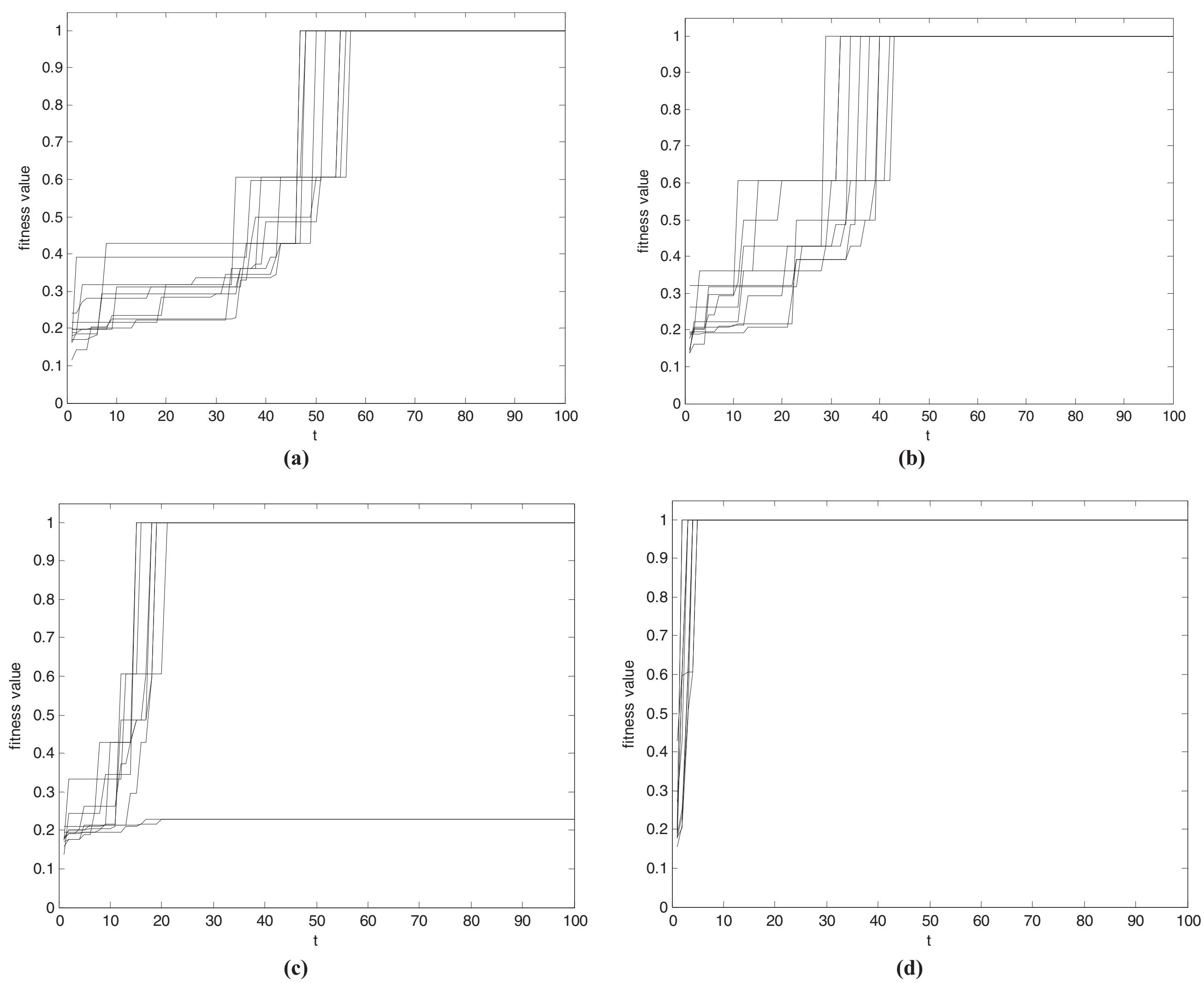
Table II Parameters for MGMPIO

Parameter	Description	value
N	The number of pigeons	150
T1	The maximum times of iteration for the map and compass operator	50
T2	The maximum times of iteration for the landmark operator	50
μ	The mean of Gaussian distribution	0
R	Variable parameter	[0.1 10]
D	The dimension of search space	2
P	The probability for Gaussian mutation	0.32
L	A set parameter for Gaussian mutation	2
A	Reference for aggregation degree	26

shows that it is more reliable than the other three algorithms. Furthermore, it is clear that, compared with other three algorithms, the MGMPIO algorithm remains its superiority in the aspects of the effectiveness and the convergence speed from Figure 6(e) and Figure 7(e).

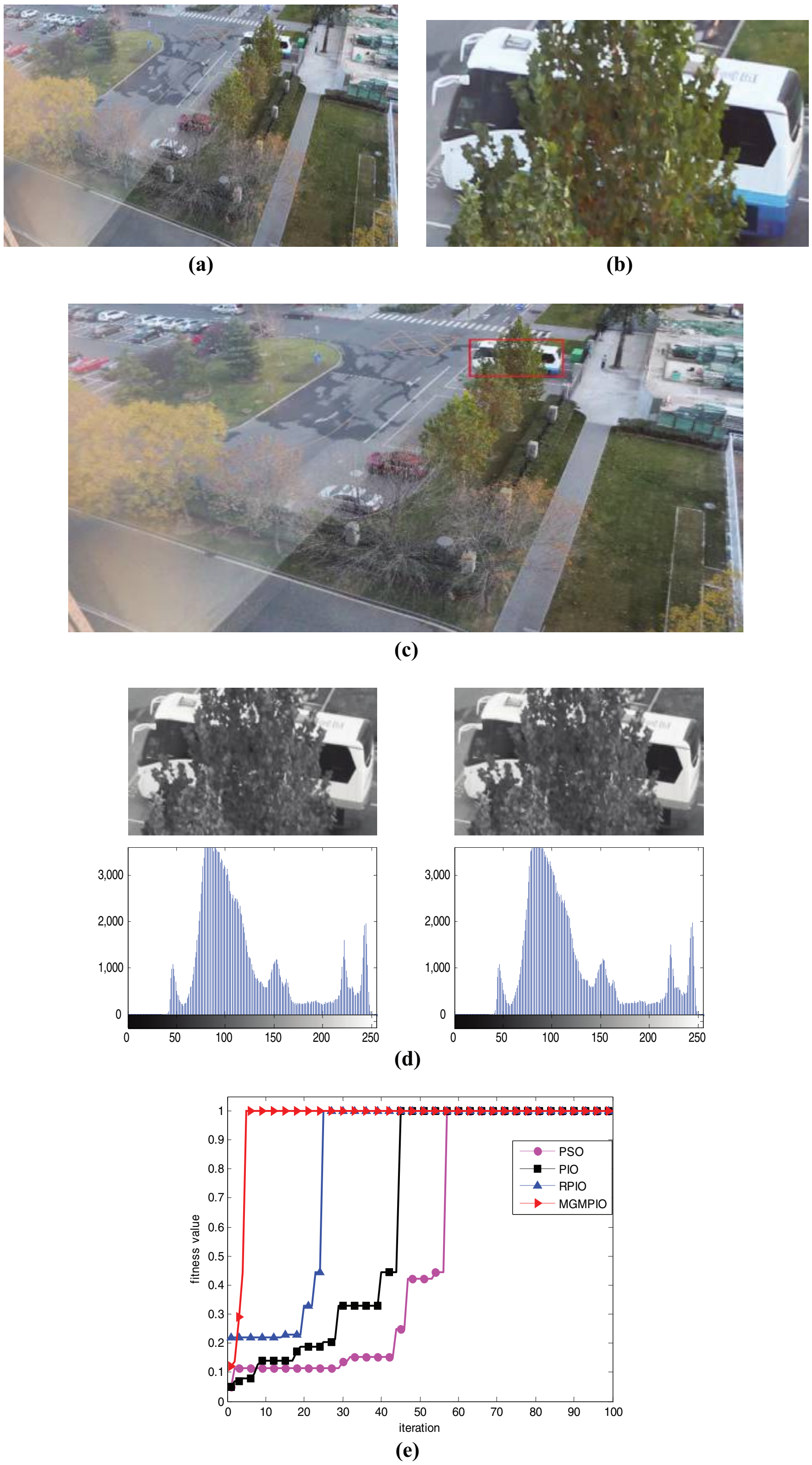
During the above three cases, MGMPIO has successfully found the global optimum that is the true position of the target with higher convergence rate. Although the original PIO has an acceptable performance compared with PSO, the efficiency of PIO is low compared with MGMPIO. An intuitive reason is that the VP mechanism is able to control the change of the previous speed inertia part in velocity updating formula (1), which can maintain a low-attenuation trend for the improved previous speed inertia part at early iterations, so that the algorithm possesses a stronger global search ability to enhance the probability of finding the range of global optimal position accurately. At the same, at the late of iterations, the rapid attenuation trend for the improved previous speed inertia part

Figure 5 Results of run 10 times for Case 1



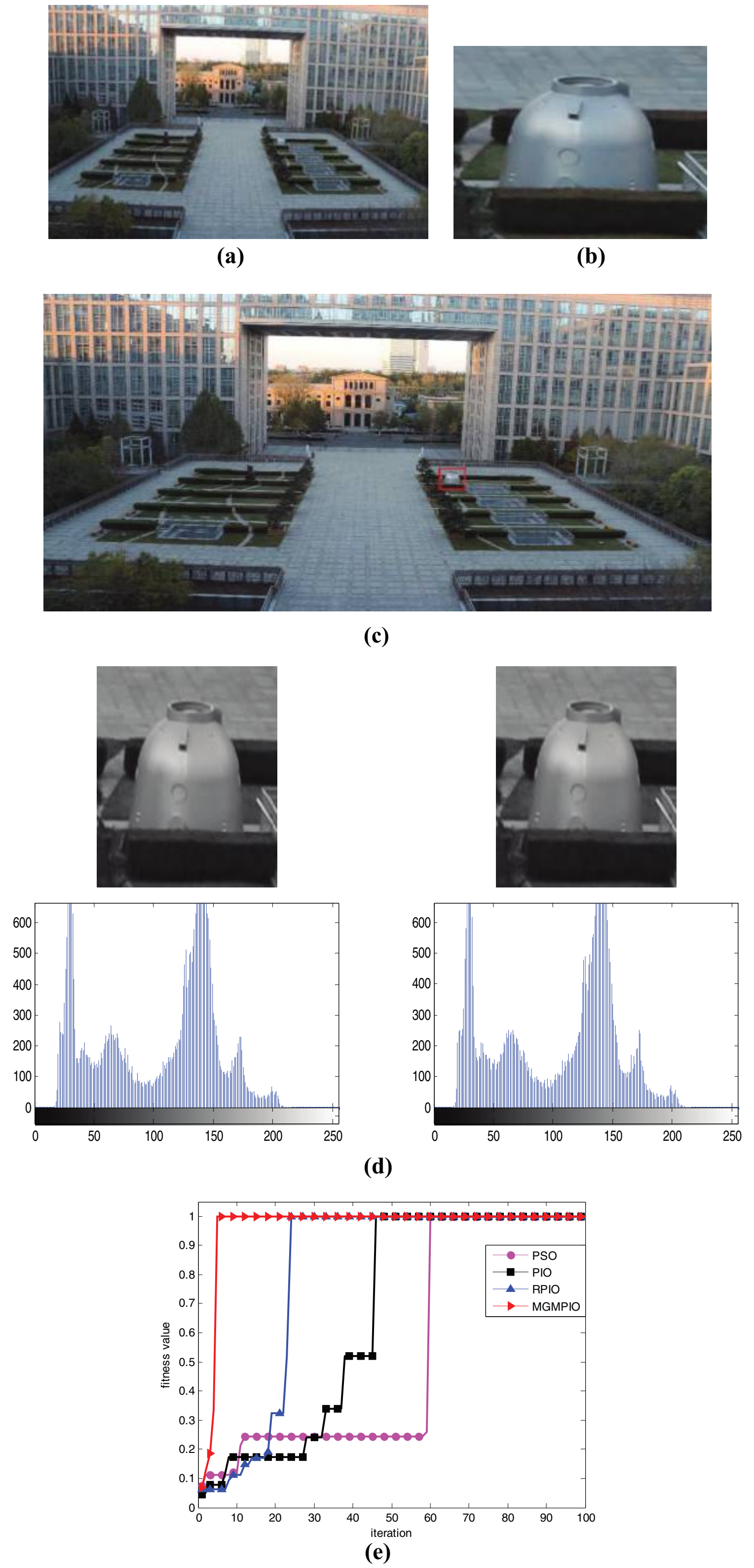
Notes: (a) Evolutionary curves with PSO; (b) evolutionary curves with PIO; (c) evolutionary curves with RPIO; (d) evolutionary curves with MGMPIO

Figure 6 The experimental results of image matching for Case 2



Notes: (a) Original image for Case 2; (b) template image for Case 2; (c) results for image matching; (d) the histogram of image that has been matched successfully and template; (e) evolutionary curves with PSO, PIO, RPIO and MGMPIO

Figure 7 The experimental results of image matching for Case 3



Notes: (a) Original image for Case 3; (b) template image for Case 3; (c) results for image matching; (d) the histogram of image that has been matched successfully and template; (e) evolutionary curves with PSO, PIO, RPIO and MGMPIO

is obtained. Thus, the algorithm can find the global optimal position quickly on the basis of finding the range of the global optimal position, speeding up the convergence speed of the basic PIO algorithm. In addition, the MGM mechanism is able to make the individual with low fitness value has a greater probability to locate other locations of the searching space to search and the individual with low fitness value carry further search to all around the current position, which not only can enhance the probability of getting rid of local optimal position, but also accelerate the convergence rate of the algorithm. It is observed that RPIO has enhanced the robustness of the original PIO, and MGMPIO has further enhanced the robustness of the original RPIO. The fast convergence speed of an algorithm is crucial for image matching, particularly in aerial images with complex backgrounds. Based on an overall consideration of experiments in the above three groups, the proposed MGMPIO algorithm is superior to three evolutionary algorithms in solving image matching problem.

Conclusions

In this paper, the MGMPIO algorithm is proposed to accomplish the image matching problem, which combines the VP mechanism and the MGM mechanism. The VP mechanism helps to improve convergence speed and enhance the probability of finding the optimal location. The MGM mechanism contributes to jumping out of the local optimum and preventing from falling into local optimum. The experimental results in three test cases show that the MGMPIO algorithm can successfully find the optimal solution during every run, and it markedly improves the performance of the original PIO algorithm in terms of convergence speed, robustness and stability. Compared with the RPIO algorithm, MGMPIO also shows a better stability by using the MGM mechanism, which provides a more perfect way for the image matching problem. The MGM mechanism used in this paper can enhance the probability of jumping out of local optimal position and accelerate the convergence speed. But, according to the principle of the MGM mechanism, when there are several objects similar to the template image in original image, it will be not sure to find the optimal solution accurately. Therefore, further improvements should be made in the future work. We will be more focused on balancing the convergence speed and accuracy of the algorithm. Moreover, as the uncertainty of the variation, when the search space is large enough, the matching difficulty will get larger. We will also focus on the study of better methods for strengthening stability and enhancing searching ability. We will also apply the proposed approach to solve other real-world problems, such as UAV, mobile robots, industry production line and intelligent transportation.

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Further reading

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About the authors

Shanjun Chen received his BS degree in Automation Science and from the University of Science and Technology Beijing, China, in 2015. He is currently a master candidate with the School of Automation Science and Electrical Engineering, Beihang University. He is a member of Bio-inspired Autonomous Flight Systems (BAFS) Research Group of BUAA. His current research interest includes advanced flight control, computer vision and bio-inspired computation.

Haibin Duan is currently a full professor of School of Automation Science and Electrical Engineering, Beihang University (formerly Beijing University of Aeronautics and Astronautics, BUAA), Beijing, China. He is the head of Bio-inspired Autonomous Flight Systems (BAFS) Research Group of BUAA. He received the PhD degree from Nanjing University of Aeronautics and Astronautics (NUAA) in 2005. He was an academic visitor of National University of Singapore (NUS) in 2007, a senior visiting scholar of the University of Suwon (USW) of South Korea in 2011. He is currently an IEEE Senior Member. He has published three monographs and over 70 peer-reviewed papers in international journals. His current research interests include bio-inspired computation, advanced flight control and bio-inspired computer vision. Haibin Duan is the corresponding author and can be contacted at: hbduan@buaa.edu.cn