Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 8039589, 10 pages
https://doi.org/10.1155/2022/8039589

Research Article

Simulation of Multimedia Visual Image Motion Track Marking Based on Artificial Bee Colony Algorithm

Wei Chen

College of Computer Science and Technology, Huaqiao University, Xiamen, Fujian 361021, China

Correspondence should be addressed to Wei Chen; 12310@hqu.edu.cn

Received 9 May 2022; Revised 17 June 2022; Accepted 21 June 2022; Published 30 July 2022

Academic Editor: Sagheer Abbas

With the rapid development of electronic technology, network technology, and multimedia processing technology, people pay more and more attention to the surrounding environment. Paying attention to and handling emergencies have also become one of the main points of attention. Through the combination of multimedia and monitoring system, the collected image data are processed and integratedly controlled by the computer platform, and an intelligent monitoring system for traffic road safety can be obtained. Due to the advantages of multimedia visual image motion trajectory identification technology in road traffic safety, it can effectively prevent the chaos and influence caused by humans in chaotic situations, making it widely used. By identifying the motion trajectories of different objects, road emergencies can be effectively prevented and countermeasures can be established. Based on this, this study proposes the artificial bee colony (ABC) algorithm to identify the motion trajectory in the visual image, but the standard ABC algorithm is too slow to converge in the later stage of trajectory recognition. Therefore, this study is based on the standard ABC algorithm. The trajectory recognition simulation shows that the optimized algorithm accelerates the convergence speed and the ability of the global optimal solution in the trajectory recognition process. Then, the optimized ABC algorithm is used to identify the multimedia visual image trajectory. The experiment shows that the average correct rate of feature extraction is also about 98%. The data identification results also show that the optimized ABC algorithm fits the real trajectory better in the trajectory identification. The running time of the algorithm is shorter than the running time of other comparison algorithms, which fully shows the accuracy and superiority of the algorithm in this study.

1. Introduction

Digital image processing technology is developed with the development of computer technology, artificial intelligence, and multimedia technology. The earliest digital image processing is to shorten the transmission time after digital compression. With the development of computer technology and artificial intelligence, people have begun to study the use of computers to interpret images and try to use the vision and thinking of computational computers to observe and understand images beyond human vision. The detection and tracking of objects in a video are key elements of current image and video processing. It bridges the transition from the lower-level to the higher-level semiconductor characters in image processing, as well as laying the foundation for intelligent video understanding. Typically, there are video scenes consisting of background and objects, where the objects are an important part of the video sequence and contain key information. Therefore, fast and efficient segmentation of objects in a video and tracking of objects of interest is the basis for subsequent analysis of the video.

With the rapid development and popularization of information security systems and networks, multimedia information becomes more and more abundant, and all kinds of information people receive are multimedia data. How to organize, represent, store, manage, query, and retrieve these multimedia data is a major challenge to traditional database technology. In multimedia data, image and video data are the main carriers of visual information. Therefore, the intelligent analysis and processing of video data, as well as the faster and more accurate detection of the interaction points between users and the increasing multimedia database, are the research focus of many scholars at this stage.

At present, the analysis and research of video content are generally based on specific application fields and uses and have not formed a complete structure. On the basis of literature research, in this study, the improved manual swarm approach avoids trapping in partial best and further improves its convergence and precision. From the research results, the improved algorithm in this study has a relatively stable detection effect.

2. Related Work

The detection and tracking technology of moving objects has been a key topic of research within the domain of multimedia computer visualization. Previously, artificial bee colony algorithms have been used for robot motion planning with various adaptations to different problems. Scholars in various countries have explored their corresponding applications. Liu et al. proposed a novel RG-based version of thresholded VSS featuring better quality of vision and lossless recovery. Random occlusion was utilized for enhancing optical performance and reducing darkness in the concealed images rebuilt [1]. Wang et al. proposed a new Doppler fuzzy solver (DAR) for synthesizing aperture radiation (SAR) in the image domain of terrestrial mobile objectives. Compared with the existing 2D time-domain DAR, this algorithm performs better in the most common signal-to-noise ratio cases [2]. Ashiba presents an excellent method for infrared (IR) image enhancement. Simulation results show that the method successfully improves the quality of IR images [3]. Ywa et al. combined the algorithm of artificial bee colony (ABC) and back propagation neural network (BPNN) in a rainfall forecasting program to determine the distribution characteristics of precipitation in the time and frequency domains for various temporal scales and reveal the interannual trends and anomalies of precipitation in the basin [4]. Chen et al. proposed the use of manual swarm (ABC) to perform argument recognition. He obtained robot dynamic parties by means of the ABC method. Thus, effective dynamic parametrizations could have been acquired by the ABC method and the peak values of errors on the predicted torsional curves were suppressed through the compensation model [5]. Zachary was the first researcher who studied the track trajectories of the balls on the globe. For this purpose, he extracts an exact model of the ball-on-sphere system and uses an artificial swarm algorithm to tune the fuzzy membership parameters with the aim of minimizing the aforementioned objective function [6]. The swarm cognitive behavior of honey bees can be easily replaced by swarm intelligence with “social cognition.” Sung-Soo proposed a new manual bee colony clustering algorithm (ABCC), and simulation shows that this proposed clustering algorithm proves to be superior to other methods with an increasing node count of a web [7]. Stün proposed an efficient motion compensation (MC) scheme based on multicriteria decision-making, which uses surrogate-based optimization (SBO) to minimize entropy and maximize image sharpness to remove blur in images [8]. Gultekin defines a new performance metric. He ranks these algorithms based on new metrics and metrics from an image analysis based on image quality in a study in the library, demonstrating by experiment the available metrics might have not been a great way to measure the performance of the algos [9]. Liu aims the optimization of the motion planner algorithm using a motion planning pipeline and a planning request adapter, for example, to optimize the sample-based motion planning algorithm. Experimental results show that the optimized algorithm increases the planning time but significantly improves the efficiency [10]. The research results of the above scholars are only partially relevant and suggestive to the research topic of this study. In some cases, the optimization performance of the optimization method may not be as good as the original algorithm in more complex scenarios.

3. Multimedia Image Processing

In order to better identify the motion trajectories of multimedia visual images, this study describes the preprocessing methods for video images and details the transformation relationships between the artificial bee colony (ABC) algorithms used, as well as the implementation process of the ABC algorithm.

3.1. Video Image Preprocessing. The purpose of preprocessing video images is to remove noise in the image or to make it easier to extract some image features that are not easy to be extracted. Image preprocessing in the system mentioned in this study is to extract moving objects more accurately [11–13]. The preprocessing methods used in this system are discussed separately below.

The moving image of the moving object is binarized, that is, the process of presenting the entire image with an obvious black and white effect. This process is conducive to further processing the image, making the image simpler, further reducing the amount of data, and highlighting the outline of the target of interest:

$$R_{d+1}(v,\vartheta)=\begin{cases}1, \left[T_d(v,\vartheta)-J_d(v,\vartheta)>E_f\right]\\ 0,\end{cases}\tag{1}$$

The threshold for binarization in the equation is expressed as E_f; while $T_d(v,\vartheta)$ and $J_d(v,\vartheta)$ represent the current image and background of the moving object in the view.

Then, the background adaptive update algorithm is introduced to suppress the influence of illumination and background transformation [2, 14]. The equation is as follows:

$$\begin{gathered}J_{d+1}(v,\vartheta)=\begin{cases}T_d(v,\vartheta)+\theta\left[J_{d+1}(v,\vartheta)-T_d(v,\vartheta)\right]\\ \text{if } R_{d+1}(v,\vartheta)=0\end{cases},\\ J_{d+1}(v,\vartheta)=\begin{cases}T_d(v,\vartheta)+\varphi\left[J_{d+1}(v,\vartheta)-T_d(v,\vartheta)\right]\\ \text{if } R_{d+1}(v,\vartheta)=0\end{cases}\end{gathered}\tag{2}$$

Among them,

$$\theta, \quad \varphi \in [1, 0]. \tag{3}$$

To address the effects imposed from the target object, an adaptive threshold filter is introduced to process the image after the background update. Assuming that the threshold value of the target boundary length K is F_s, then the equation is expressed as follows:

$$Fs = Kf_{st} \times \alpha + K_{snd} \times \beta. \tag{4}$$

In the above equation, in the multimedia image, K_{fst} represents the perimeter of the maximum motion of the target, K_{fst} represents the perimeter of the next level, and α and β represent the weighting coefficients of the two, respectively.

Assume that the judgment threshold for the lowest noise is $P_{\min}$ if

$$K_{fst} > P_{\min}. \tag{5}$$

The extraction is performed if

$$K_{fst} \leq P_{\min}. \tag{6}$$

Then, the image target will not be extracted.

Assuming that the threshold Ps in the multimedia view is smaller than the perimeter of the nth moving object, that is,

$$K_n > P_s. \tag{7}$$

The picture traits are pulled out in such situations; otherwise, they will be discarded.

3.2. Artificial Bee Colony Algorithm. As a very new swarm intelligence algorithm, the artificial bee colony algorithm has been widely used to solve practical problems after it was proposed. For example, the improved bee colony algorithm has been researched by some scholars for the path planning of unmanned boats; in the process of information exchange of the algorithm, the chaotic sequence method is used to initialize the picking bees, so that the algorithm can get rid of the local optimum.

The artificial bee colony algorithm is derived by mimicking the way bee colonies search for the best source of honey in the biological world. Honeybees realize the transmission of information through different divisions of labor, as shown in Figure 1. Information sharing between bee colonies is conducive to finding the best nectar source and better maintaining the reproduction and survival of bees.

In the ABC method, the three bees will be converted to each other according to the income of the nectar source. (1) When the income of the nectar source is too low, all of them will be converted into scout bees to find new nectar sources. (2) When the nectar source income meets the requirements of the follower bee transformation, it will be converted into a follower bee and share the nectar source information. (3) When the income from the nectar source meets the conditions for transforming the bees, it will be transformed into a bee and guide other bees by sharing the information of the nectar source.

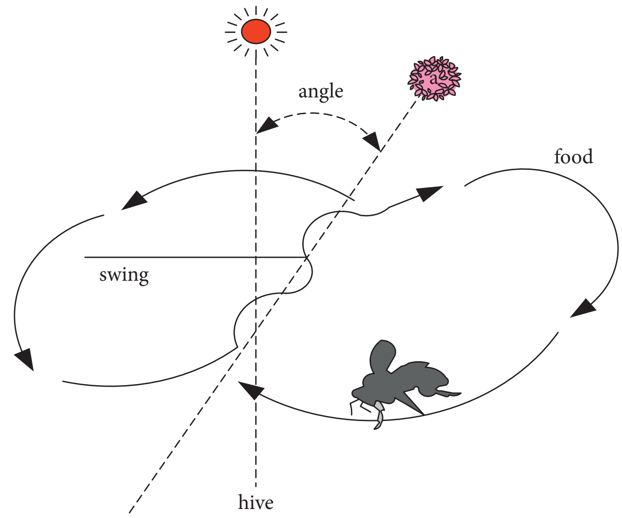


Figure 1: Schematic diagram of the flight of bees.

On the basis of previous research, this study applies the artificial bee colony algorithm with good global convergence and high solution accuracy to the problem of multimedia visual image motion trajectory identification and proposes a multimedia visual motion based on the artificial bee colony algorithm and track identification method.

The shadow and random noise of the target motion trajectory in the multimedia visual surveillance image are mainly determined by the relevant parameters of the target object. In order to better judge the pros and cons of the solution obtained by the function, before the ABC algorithm runs, it is necessary to choose to initialize the bee colony. Initialization is to arrange all bees in the population to different nectar sources in a random way. The population size of bees is denoted by N. The nectar source position of each individual bee in the colony during the initialization process can be expressed as follows:

$$A_{mn} = A_n^{\min} + \left(A_n^{\max} - A_n^{\min}\right) \cdot {}_{\text{rand}}(0, 1). \tag{8}$$

The upper and lower constraints of the nth parameter in the equation are denoted as $A_n^{\max}$ and $A_n^{\min}$, respectively. Among them, $m = 1, 2, \ldots, i$, $n = 1, 2, \ldots, j$. Each function solution corresponds to a j-dimensional solution vector.

The fitness function value of the nectar source position is calculated; that is, the lowest noise judgment threshold in the multimedia visual image is as follows:

$$\mathrm{Fit}_i = \begin{cases} \dfrac{1}{(1 + F_i)}, & F_i \geq 0 \\ 1 + |F_i|, & F_i > 0 \end{cases} \tag{9}$$

Among them, the function solves the judgment threshold in the multimedia visual image corresponding to the F_i table.

The picking bees continue to mine new honey sources W_{mn} around the current honey location, and at the same time, the suitability function value of the new honey source location is calculated. The fitness function values of the original nectar source and the new nectar source are compared, and a better nectar collection location is chosen. That is, the target motion track record is updated according to the matching result, so as to achieve the purpose of identifying the target motion track:

$$W_{mn} = A_{mn} + \beta_{mn} \cdot (A_{mn} - A_{Rn}). \tag{10}$$

In the equation, n represents a random integer, R is a random integer different from m, and β_{mn} is a random number of $[-1, 1]$. Among them, $m = 1, 2, \ldots, i$, $R \in \{1, 2, \ldots, i\}$, $n \in \{1, 2, \ldots, j\}$.

When the exploration range of bees exceeds the search space, the nectar source location is selected according to the following equation:

$$A_{mn} = \left\{ A_n^{\min} + {}_{\text{rang}}(0,1) \cdot \left(A_n^{\max} - A_n^{\min}\right), \quad A_{mn} < A_n^{\min}, A_n^{\max} + {}_{\text{rang}}(0,1) \cdot \left(A_n^{\max} - A_+^{\min}\right), \quad A_{mn} > A_n^{\min}. \right. \tag{11}$$

After selecting the optimal nectar source 2 location by the above-mentioned bees, the location information will be shared with the follower bees. After the follower bee judges the location information, it will follow to explore the location of the nectar according to the probability, and this probability G_n is expressed as follows:

$$G_n = \frac{\text{Fit}_n}{\sum_{i=1}^{i} \text{Fit}_n}. \tag{12}$$

In the equation, Fit_i represents the profitability of the nectar source. Through the equation, it can be seen that the profitability of the nectar source determines the selection probability. The two are positively related. That is, if the profit is large, then the contour feature of the moving target is extracted; on the contrary, it is discarded.

The follower bee will follow the picker bee to explore the location of the nectar source by selecting the probability. At the same time, it will also search the neighborhood of the nectar source according to the greedy criterion and then select it according to the probability, until all the selections are completed and then enter the next stage.

The limit number of times that the same nectar source is mined by the same bee is set. When the number of times is reached but not selected, the nectar source position will be abandoned; that is, all the objects in the multimedia visual image will not be extracted. It transforms into a scout bee looking for a new location, and the equation is expressed as

$$W_n = A_n^{\min} + \left(A_n^{\max} - A_n^{\min}\right) \cdot_{rand} (0, 1). \tag{13}$$

Among them, $n = 1, 2, \ldots, i$.

According to the analysis of the above key stages, the three bees of the ABC algorithm perform their respective duties and cooperate with each other, which are all indispensable parts of the algorithm. The cooperation of the three bees makes the ABC algorithm have better optimization ability and faster convergence speed than other swarm optimization algorithms. A flowchart of the algorithm is shown in Figure 2.

Compared with other intelligent algorithms, the ABC algorithm has relatively few parameters, has a very high fitness, is easier to understand and operate, and has strong robustness. As the standard ABC algorithm also has some shortcomings, such as random search with a certain probability in the search process and poor local search ability, the search accuracy cannot be guaranteed; there may be "premature" behavior of premature convergence in terms of convergence. It is very important to improve the local search capability and simplify the complexity of the manual swarm operation to improve the system.

4. Simulation Experiment of Multimedia Visual Image Movement Track Marking Based on Artificial Bee Colony Algorithm

4.1. Path Planning Based on Manual Swarm Operation

4.1.1. Algorithm Improvement. In the standard ABC algorithm, the greedy criterion for bees to search for the location of new nectar sources is carried out by random search. Although this method has application advantages, it also has certain defects. While this method improves the algorithm's search ability, there is also a situation in which the algorithm's late convergence speed is slow. In order to satisfy both efficient search performance and fast convergence, an improvement measure is proposed: a global optimal guide term is added to the nectar source update formula of the standard ABC algorithm. The new update formula is as follows:

$$W_{mn} = A_{mn} + \beta_{mn} \cdot (A_{mn} - A_{Rn}) + \varphi (B_n - A_{mn}). \tag{14}$$

In the equation, B_n represents the value of the nth-dimensional global optimal solution; φ is a constant between [1.2, 1.8], which will increase linearly with iteration.

By adding a global optimal guide term, the global optimal information can be fully utilized in the later iteration to make the algorithm reach convergence faster and simultaneously ensure that the overall effect of the optimized method is guaranteed. The selection probability of the follower bees is proportional to the value of the nectar source fitness function, which will cause the bees to quickly fly to the nectar source position with a high fitness function value, and the algorithm is prone to "premature maturity." In order to solve the problem of prematurity of the algorithm, the study adds an opposite selection method; that is, the reciprocal value of the nectar fitness function value is proportional to the probability of following the selection of bees. The positive and negative selection methods can enable bees to have more choices of nectar sources, no longer converge toward the same nectar source prematurely and quickly, and better meet the diversity requirements of the population. The

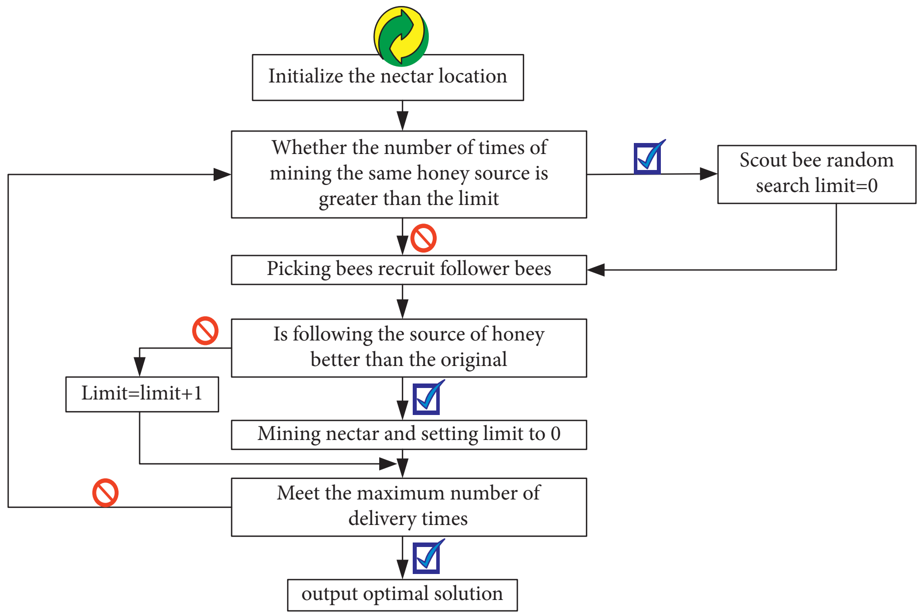


Figure 2: Schematic diagram of artificial bee colony algorithm flow.

reverse selection probability is given by the following equation:

$$G_n = \frac{(1/\mathrm{Fit}_n)}{\sum_{i=1}^{i} \mathrm{Fit}_n}. \tag{15}$$

According to the above equation, the probability selection position n is selected, and the nectar source positions m and n are updated and searched successively.

The process diagram of the improved ABC method is shown in Figure 3.

To test the effectiveness of the algorithm, the performance of the modified ABC algorithm is compared with that of the standard ABC algorithm, and the simulation curves are shown in Figure 4; they are the iterative convergence curves of the standard ABC operator and the iterative convergence curves derived from the modified ABC operator. The simulation optimization data are summarized in a table, and the statistical results are listed in Table 1.

Figure 4(a) shows the convergence curve with an unoptimized manual bee swarming operation and Figure 4(b) shows the convergence curve with the optimized bee swarming algorithm. Due to the early maturity nature of the traditional human swarming operation, it cannot quickly converge to the optimal solution in the later stage. It is obvious from the comparison graph that the unimproved algorithm converges slowly, while the improved iteration speed and cost value of the modified one increase and converge faster.

Combining the data in Table 1, it can be clearly seen that in the 100 iterations of the traditional algorithm, the convergence begins at 92 times, the iteration cost is 150, the cost value is high, and the effect is not ideal. The improved algorithm starts to converge on the 79th, an increase of about 14%. The consideration value was 143.8, an increase of about 5%. After validation, the improvement of the update

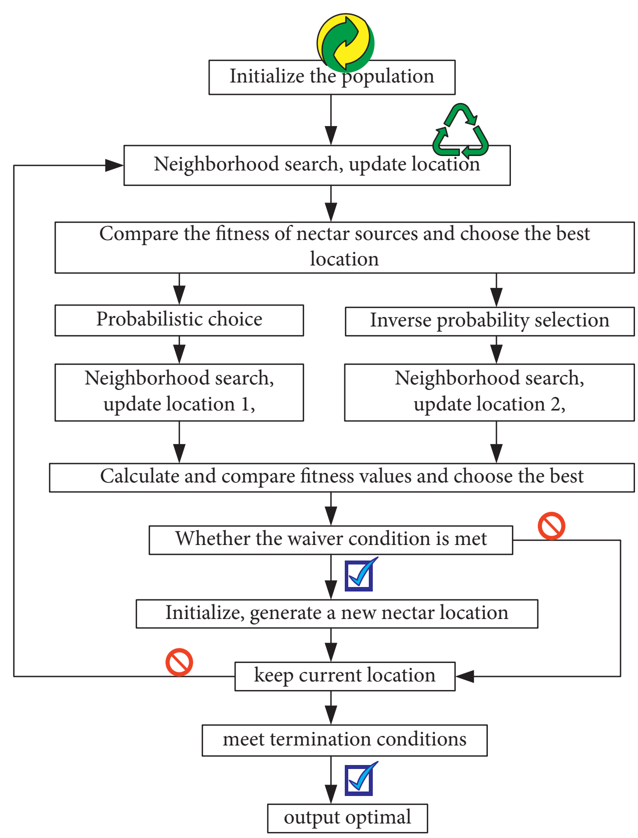


Figure 3: Flowchart for an enhanced human swarming alpha method.

equation of standard manual honeycomb method by adding the global optimal bootstrap term and probabilistic selection mechanism better accelerates the ability of the algorithm toward the global best problem solution conversion.

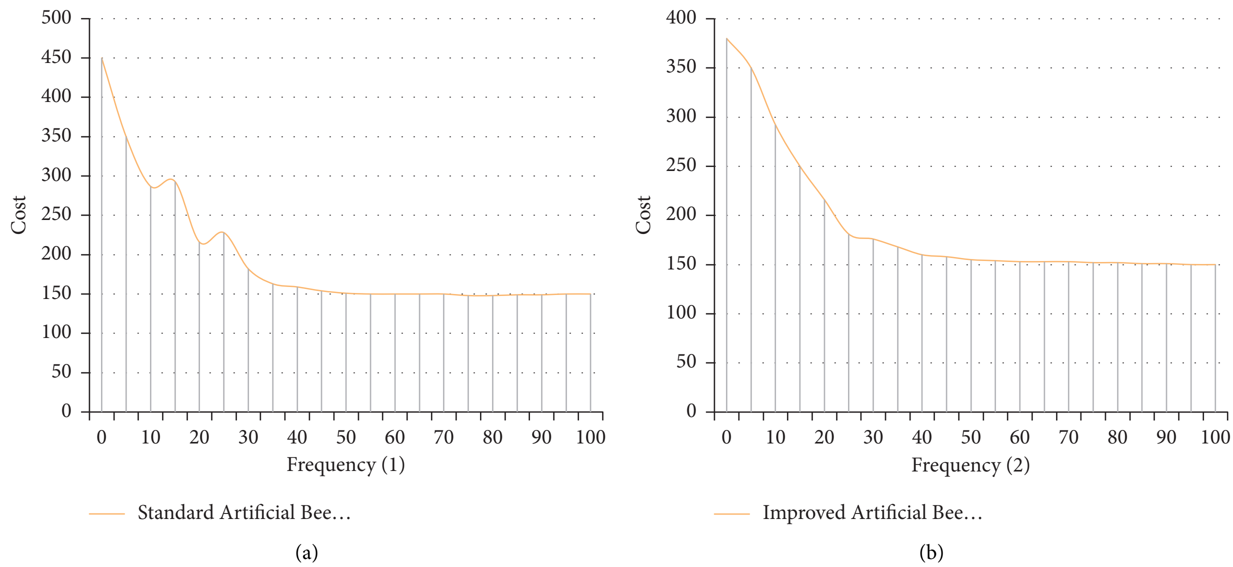


FIGURE 4: Comparison of iterative convergence between the unimproved algorithm and the improved algorithm.

TABLE 1: Optimization result data.

Algorithm	Standard bee colony algorithm	Improved bee colony algorithm
Average time-consuming (s)	0.509	0.6
Convergent mean	150	143.8
Mean convergence algebra	92	78.5

The Effect of Parameter Changes on the Algorithm. It is assumed that the flight radius of the bees in the experiment is m = 10. The parameter α that controls the threshold is 0.1 (the value of α is between [0, 1]), and the number of scout bees is n = 3. The initial factor θ, and then observe the effect of changes in α and θ on the algorithm time-consuming. The statistical results of the two parameter changes are shown in Figure 5.

Figure 5(a) shows the effect of the parameter θ on the improved ABC algorithm, and Figure 5(b) shows the effect of the parameter α on the improved ABC algorithm. From the trend of the data in the figure, under the transformation of the parameter θ, the time consumed by the algorithm operation has changed accordingly, but in general, the change of the parameters has a more obvious impact on the data. The change in the parameter α, as is evident from the data trend, shows an upward trend in the running elapsed time. The effect on the running time is much more significant. In general, the change of parameters has a certain influence on the trajectory recognition results of the algorithm. Changes in parameters should be noted in the experimental design.

4.1.2. Motion Track Marking Method Using ABC Algorithm. Under normal circumstances, assuming that the total number of bees1 in the manual swarm method is equal to the total number of slave bees2, which is equal to the total amount of bees3; that is, it is halved:

$$C_e = G_e = \frac{1}{2}M_e. \tag{16}$$

The population of bees is represented as $Z = \{Z_1, Z_2, \ldots, Z_i\}$, which is initialized:

$$Z_m^n = Z_{\min}^n + {}_{\text{rand}}(0,1)\left(Z_{\max}^n - Z_{\min}^n\right). \tag{17}$$

Among them, ${}_{\text{rand}}(0,1)$ represents the neighborhood search speed of the bee colony.

Assuming that the variable of the target in the multimedia view is K, and the degree of variance is expressed as $\text{Kurt}(K)$, then

$$\text{kurt}(K) = U\left[K^4\right] - 3\left(U\left[K^2\right]^2\right.. \tag{18}$$

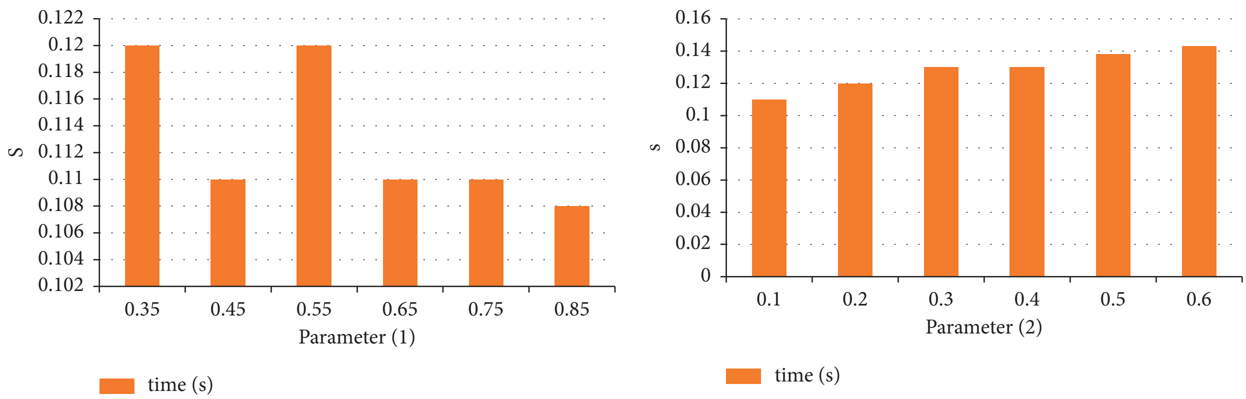
In the equation, U is the target pixel energy in the view.

The objective function of the independent analysis component of the image motion trajectory is that the variosity is used, assuming that the i sequence image signal vector collected by the camera is as follows:

$$A(s) = \left[A_1(s), A_2(s), \ldots, A_i(s)\right]^s. \tag{19}$$

Then, in the case that the separation vector is represented as ϑ in the view, the calculation equation of the separated target signal $B(s)$ is as follows:

$$B(s) = \vartheta A(s). \tag{20}$$



(a)

(b)

FIGURE 5: The effect of the values of α and θ on the algorithm.

Then, the location of the nectar source is updated, the probability selection of the following bees is calculated, and by limiting the number of searches, to give up the unmatched nectar source, the new nectar source location is found at the same time; the judgment formula that satisfies the output condition is as follows:

$$\mathrm{M}_{ax} > \mathrm{l}_{im}. \tag{21}$$

Among them, M_{ax} is the maximum proxy condition and l_{im} is the maximum limit threshold of the swarm search.

Environmental Suitability Comparison. In order to further test the environmental adaptability and convergence speed of the artificial bee colony method, the artificial bee colony algorithm is used to identify the same trajectory in different scale environments. In the simulation experiment, four grid environments of 50×50, 70×70, 100×100, and complex grid environments are used as test objects. Taking the standard ABC algorithm and the improved ABC algorithm as a comparison, the statistics of the time consumption results of the trajectory recognition are shown in Figure 6.

The trajectory recognition running time of the two algorithms in different environments is shown in Figure 6. The comparison results of the trajectory recognition time-consuming of the two algorithms show that in the 50×50 grid environment, the time-consuming of the improved ABC algorithm in this study is 0.005 seconds. In a complex obstacle environment, it takes 0.02 seconds. The standard algorithm's trajectory recognition time in these two environments is 0.01 seconds and 0.035 seconds. The experimental results show that the improved algorithm in this study has a short trajectory recognition time and better effect.

The above experiments demonstrate that the optimized ABC algorithm has better environmental adaptability and convergence speed in trajectory recognition for better results in practical application cases.

4.2. Motion Track Marking by Manual Swarm-Based Method

Simulation Experimental Design. On the basis of image preprocessing, in order to better detect the recognition effect of motion trajectory of ABC algorithm, the motion trajectory in Figures 7 and 8 is used as the exploration sample, and the Win7 Intel E5200 processor with a 64-bit operating system is used as the experimental platform to extract the motion trajectory features of graphics under the restriction.

The other two trajectory extraction methods are selected as the comparison objects of the labeling method in this study, and the extraction effect of the graph and the motion trajectory features of the graph are compared through the following four evaluation indicators.

First is the feature extraction rate Dr of motion images, which mainly indicates the ratio that the number with features SD to the total number with features ZD of image motion trajectory in a certain time:

$$Dr = \frac{SD}{ZD} \cdot 100\%. \tag{22}$$

The second is the false alarm rate HAF for the feature extraction of moving images, which mainly represents the ratio of the number of wrongly extracted features CN to the total number of features ZD:

$$HAF = \frac{CN}{ZD} \cdot 100\%. \tag{23}$$

The third is the correct rate ZH of the feature extraction of the moving image, which mainly represents the ratio of the number of samples Z_t to the total number of samples H_t for the correct feature extraction of the motion trajectory of the image in the experimental samples:

$$ZH = \frac{H_t}{Z_t} \cdot 100\%. \tag{24}$$

The fourth is the time s consumed by extracting features.

Analysis of Image Trajectory Recognition. With the improved ABC algorithm, the video images are analyzed for trajectory recognition, and the evaluation indexes are calculated based on the above calculation method. The statistics of the trajectory recognition test results in Figures 7 and 8 are shown in Table 2.

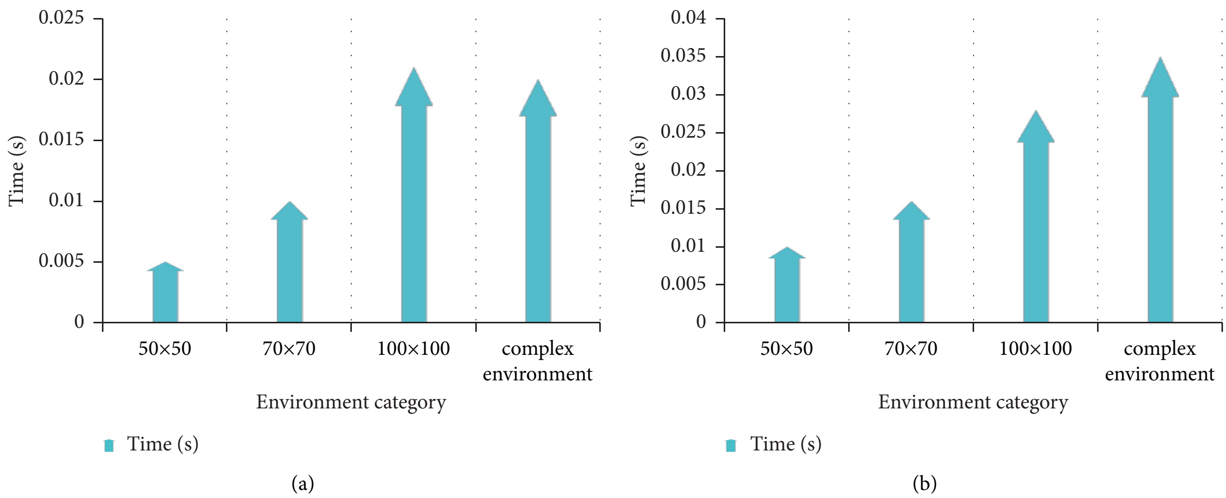


Figure 6: Path planning results in different environments.

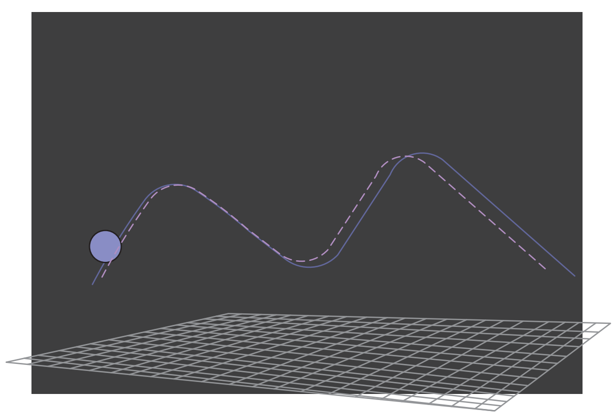


Figure 7: Test image with noise and shadows.

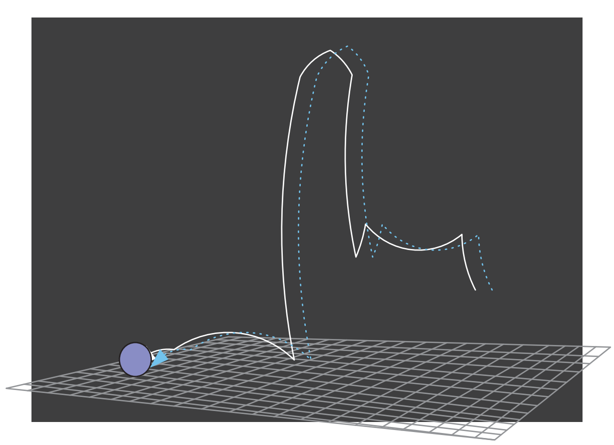


Figure 8: Test image with noise and shadows.

Table 2 lists the data comparison between the algorithm in this study and the other two comparison algorithms in four aspects: extraction probability, false alarm rate, correct rate of feature extraction, and time-consuming when extracting image features. The results show that the feature extraction rate for the trajectory recognition in Figures 7 and 8 under the method in this study is above 96%, and the false alarm rate is almost negligible, both below 1.3%, which has little impact on the recognition of trajectory features. The correct rate of feature extraction is also above 98%, which further shows the superiority of the algorithm in this study.

Table 2: Performance statistics of different methods.

		Dr (%)	HAF (%)	ZH (%)	*s*
Method 1	Figure 7	91.4	6.3	91.2	7.7
Method 2		92.6	7.3	90.8	5.5
The method of this study		96.9	0.9	99.1	1.7
Method 1	Figure 8	88.7	7.5	89.4	9.8
Method 2		90.5	6.1	88.2	7.9
The method of this study		96.6	1.1	98.4	2.2

Image Track Recognition Comparison Results. Figures 7 and 8 are also used as the samples of this investigation, and the identification results of the method in this study and the other two comparison methods are statistically analyzed.

Figure 9(a) shows a comparison diagram of the track identification effect in Figures 7, and Figure 9(b) shows a comparison diagram of the track identification effect in Figure 8. It can be seen from the data trend of the identification that whether it is Figure 7 or the more complex Figure 8, the data identification results are that the trajectory identification method in this study is more suitable for the real trajectory, which further shows that the accuracy rate of the method in this study is higher.

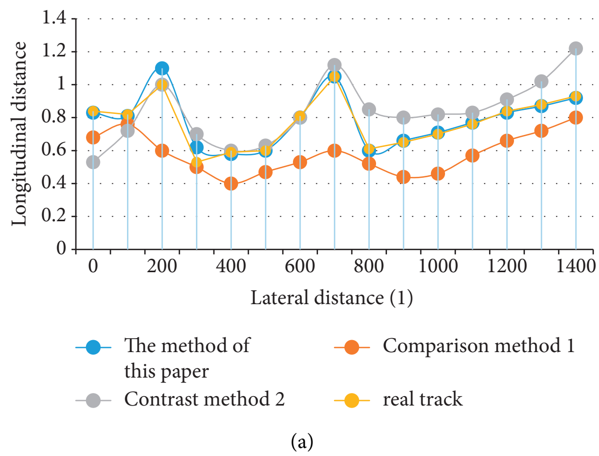


Figure 9: The effect of different methods on the trajectory identification of graphs and graphs.

5. Conclusion

In this study, a method for identifying multimedia visual motion trajectory based on the artificial bee colony algorithm is proposed, and the objective function of independent component analysis of multimedia visual image motion trajectory features is optimized and solved, and the successful identification of multimedia visual image motion trajectory is realized. The ideal experimental results were obtained. By imitating the biological characteristics of bees, the algorithm divides bees into three categories according to their division of labor: guiding bees and following bees to scout bees. The mutual transformation and information transfer between the bee colonies are eliminated, and the optimal result of path identification is obtained. However, the traditional bee colony algorithm has the defects of slow convergence speed and easy to fall into the global optimum in the later stage of the trajectory identification process. In order to solve this problem, this study optimizes the bee colony algorithm by adding a global optimal guide The simulation experiment of trajectory recognition is carried out to compare the algorithms before and after optimization. The simulation results show that the optimized algorithm in this study accelerates the convergence speed in trajesctory recognition and has strong environmental adaptability. It is applied to the actual simulation case to identify the motion trajectory in the multimedia video image, and compared with other trajectory recognition methods. The simulation results show that the optimized bee colony algorithm has a higher degree of fitting and more advantages.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

References

[1] X. Liu, S. Wang, and X. Yan, W. Zhang, Random grid-based threshold visual secret sharing with improved visual quality and lossless recovery ability," *Multimedia Tools and Applications*, vol. 77, no. 16, Article ID 20673, 2018.

[2] Z. R. Wang, J. Xua, Z. Z. Huang, X. D. Zhang, X. G. Xia, and T. Long, "Road-aided Doppler ambiguity resolver for SAR ground moving target in the image domain," *IEEE Geoscience and Remote Sensing Letters*, vol. 13, no. 10, pp. 1552–1556, 2017.

[3] H. I. Ashiba, H. M. Mansour, H. M. Ahmed et al., "Enhancement of IR images using histogram processing and the Undecimated additive wavelet transform," *Multimedia Tools and Applications*, vol. 78, no. 9, Article ID 11277, 2019.

[4] B. Ywa, L. A. Jian, and L. A. Rong, "Precipitation forecast of the Wujiang River Basin based on artificial bee colony algorithm and backpropagation neural network," *Alexandria Engineering Journal*, vol. 59, no. 3, pp. 1473–1483, 2020.

[5] B. Chen, Y. Guan, and H. Wu, "Joint robot dynamics model identification based on artificial bee colony algorithm," *Nanjing Hangkong Hangtian Daxue Xuebao/Journal of Nanjing University of Aeronautics and Astronautics*, vol. 49, no. 5, pp. 736–743, 2017.

[6] E. Zakeri, S. A. Moezi, and M. Eghtesad, "Tracking control of ball on sphere system using tuned fuzzy sliding mode controller based on artificial bee colony algorithm," *International Journal of Fuzzy Systems*, vol. 20, no. 1, pp. 295–308, 2018.

[7] S. S. Kim, S. McLoone, J. H. Byeon, S. Lee, and H. Liu, "Cognitively inspired artificial bee colony clustering for cognitive wireless sensor networks," *Cognitive Computation*, vol. 9, no. 2, pp. 207–224, 2017.

[8] D. Stün and A. Toktas, "Translational motion compensation for ISAR images through a multicriteria decision using surrogate-based optimization," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 58, no. 6, pp. 4365–4374, 2020.

[9] G. K. Gultekin and A. Saranli, "Feature detection performance based benchmarking of motion deblurring methods: applications to vision for legged robots," *Image and Vision Computing*, vol. 82, pp. 26–38, 2019.

[10] S. Liu and P. Liu, "Benchmarking and optimization of robot motion planning with motion planning pipeline,"

International Journal of Advanced Manufacturing Technology, vol. 118, no. 3-4, pp. 949–961, 2021.

[11] S. Ganni and S. M. Botden, M. Chmarra, M. Li, R. H. Goossens, and J. J. Jakimowicz, Validation of motion tracking software for evaluation of surgical performance in laparoscopic cholecystectomy," *Journal of Medical Systems*, vol. 44, no. 3, pp. 56–65, 2020.

[12] L. Ozbakir and F. Turna, "Clustering performance comparison of new generation meta-heuristic algorithms," *Knowledge-Based Systems*, vol. 130, no. 15, pp. 1–16, 2017.

[13] Y. Moon and M. Lim, "Simulation analysis of prefetching image content for social networking service framework," *Multimedia Tools and Applications*, vol. 78, no. 20, pp. 28435–28452, 2019.

[14] B. Sun, Y. You, and Z. Zhang, C. Li, Modeling and simulation of an intelligent photovoltaic controller based on variable step algorithm of versoria," *Complexity*, vol. 2020, Article ID 5910430, 11 pages, 2020.