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Optimal search path planning for unmanned surface vehicle based on an improved genetic algorithm☆

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ABSTRACT

A planning model for simultaneously optimizing the unmanned surface vehicle's (USV's) direction and speed is established for searching submarines. The USV detection model is achieved through the underwater sonar search principle. An improved genetic algorithm is employed for maximizing cumulative detection probability (CDP), which uses three control factors to control the direction and amplitude of mutation adaptively and improve the convergence speed. In the simulation, the escaping target is assumed unknown direction, and many reasonable and efficient search paths are obtained. The analysis results of the evolutionary curve show that the proposed algorithm has the advantages of strong stability and fast convergence and is suitable for USV search problem.

1. Introduction

The unmanned surface vehicle (USV) is a small water surface platform with independent planning, autonomous navigation capability. The USV can perform military and civil tasks such as environmental sensing, target detection, intelligence collection, surveillance, reconnaissance, mine clearance, anti-submarine, precision strike, hydrographic survey, anti-terrorism, relay communication, and other missions. USV can use a variety of modules depending on various missions, with different sensors or execution equipment [1–3]. During the last two decades, USVs have been playing an increasingly significant role in modern marine applications. Numerous universities, research institutes, commercial entities, and military have developed their own USVs for various applications, such as natural resources exploration [4], environmental surveys [5], surveillance and reconnaissance [6], search and rescue [7].

Many studies have been carried out on USV path planning. In order to improve the accuracy and self-adaptability of USV path following, an adaptive fuzzy LOS control strategy based on the Mamdani model is proposed in [8,9] adopted multi-objective nonlinear optimization methods to solve the USV's optimal path. A path tracking control method composed of PID controllers with multiple genetic algorithm is proposed in [10] for USV speed control problem [11]. proposed a dynamic grouping strategy to enhance the collision avoidance ability of USV.

In this paper, USV's optimal search path planning for submarine search is investigated. Firstly, the motion model and detection model of USV and the motion model of the target submarine are established respectively. Then, based on the cumulative detection probability as the fitness function, an improved genetic algorithm (IGA) is employed. By introducing

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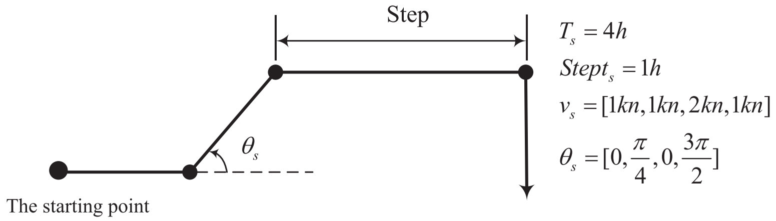

Fig. 1. Search path model.

three kinds of control factors, the algorithm adaptively controls the variation direction and amplitude to enhance the optimization ability and stability of the algorithm. Finally, simulations are conducted for analyzation, and many efficient search paths are obtained. The result proves that the algorithm can perform stability and convergence.

2. Target motion model

In continuous time and space, the references [12–14] discussed the optimal searcher path problem for stationary targets and simple directional moving targets. In this paper, the target position is assumed as a two-dimensional Markov process $\{X(t), t \geqslant 0\}$ with a state space of R^2 and a time set of $[0, +\infty]$. It means that the position of the target has no aftereffect: if the state of the target at the current time t'' is known, the probability distribution of the position at future time $t(t > t')$ is only related to the current position. However, the analytical expression of the transition probability distribution function $F(X, t|X', t')$ for a general Markov moving target is difficult to find. In this paper, we will calculate the CDP by the Monte Carlo method.

The search problem discussed in this paper belongs to the unidirectional search category in search theory: the target does not respond to the USV's behavior, and the USV's strategy does not affect the target motion. Moreover, it is assumed that the searcher and target move in two dimensions regardless of the depth effect.

3. USV model

3.1. USV motion model

In the actual search action, the search and the target usually maintain a stable movement direction and speed within a certain period of time, and adjust according to the situation at regular intervals. In this paper, the motion process with stable motion direction and speed is regarded as a step. The expression of the search path includes the following elements: the searcher start coordinate SS, the search time T_S, the stage duration Stept_S, the direction θ_S, and the speed v_S (subscript S indicates the searcher), where $\theta_S \in [0, 2\pi)$, $v_S \in [v_{\min}, v_{\max}]$. It should be pointed out that the model in this paper ignores the time spent in the direction adjustment of each stage and the resulting path deviation.

In other papers, in the optimization process of the search path, the speed of the searcher v_S doesn't change, and only the direction θ_S is regarded as a variable. In this paper, in order to be more in line with the actual situation, the direction θ_S and the velocity v_S are considered as the variables of the path optimization problem, and the stage duration Stept_S is regarded as a constant.

Fig. 1 shows a simple search path: The search time of the searcher is $T_S = 4\,\mathrm{h}$, and the duration of each stage is $\mathrm{Stept}_S = 1\,\mathrm{h}$. The speed and direction of each stage are shown in the figure. Since the search speed is considered, the 'search path' discusses here represents not only the searcher's motion trajectory but also the speed and direction information in a search scheme. For simplifying the description, the term "search path" is still used in this paper.

3.2. USV detection model

USV sonar can launch and receive sound waves along with different angles in a set sector with a certain step and order. In the practical problem, it is impossible for the USV sonar to find a submarine outside the effective range of the sonar [15,16]. There is a blind zone around the sonar working area, and the actual detection ability of the USV's sonar is decided by the effective width w of the sonar. The wider w is, the greater the sonar search ability is.

According to the geometric relationship shown in Fig. 2, the sonar effective search width can be expressed as $w = 2r\sin\beta$. Where: r represents the maximum detection distance of the sonar; β represents the single-board effective search sector angle of the sonar; α represents the single-board search fan angle of the sonar. When the distance between the target and the searcher is not greater than the effective search width w, the probability of detecting the target is 1, otherwise, it is 0. During the detection process, the model does not consider the delay of the detection signal. In each sonar detection, the searcher can immediately obtain the target state information determined by the sonar. The detection model is a two-dimensional model, regardless of the influence of the target depth on the detection. At any time t, for any searcher (X_i, Y_i),

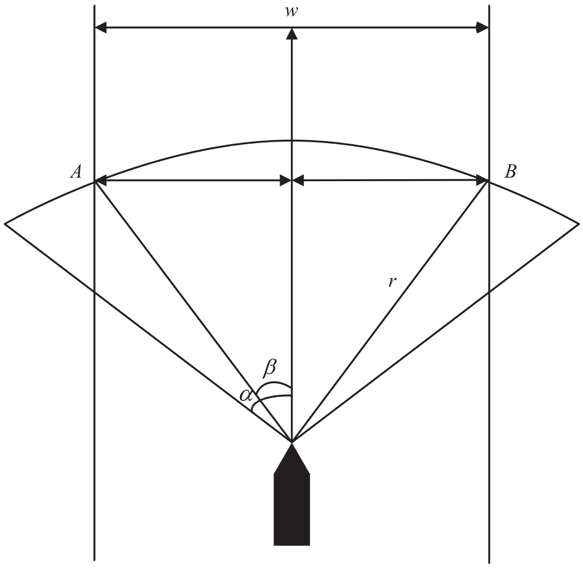

Fig. 2. Sonar effective detection width.

to search for the target (X, Y), the following formula needs be met:

$$\begin{cases} (X_i - X)^2 + (Y_i - Y)^2 \le r^2 \\ \frac{\pi}{2} - \beta \le \arctan\left(\frac{Y_i - Y}{X_i - X}\right) \le \frac{\pi}{2} + \beta \end{cases} \tag{1}$$

4. Improved mutation genetic algorithm

In this paper, the cumulative detection probability (CDP) is used to evaluate the search efficiency of the path [17], and it is used as the objective function of the search path planning and the fitness function of IGA. For any feasible search scheme ξ, the searcher's CDP in the search duration t is denoted as $F_{\text{CDP}}(\xi,t)$, and it is very difficult to accurately obtain the analytical expression of F_{CDP} for the general search path, and the Monte Carlo method is adopted for approximate calculation.

$$F_{\text{CDP}}(t) = \frac{N_D(t)}{N_T} \times 100\%, t \in [0, T_S] \tag{2}$$

Where: N_T is the total number of simulations; $N_D(t)$ is the number of detected times.

4.1. Individual coding scheme

IGA uses a single-chain real number coding scheme: each chromosome represents a search path consisting of two parts direction code and velocity of the real code. The genetic population is set as to $\text{Pop}\,(k) = \{C_1^k, C_2^k, C_3^k, \cdots C_j^k, \cdots C_M^k\}$, One of the chromosomes C_j^k is represented as $C_j^k = [|\theta_{j1}^k| \cdots |\theta_{ji}^k| \cdots |\theta_{jN}^k||v_{j(1+N)}^k| \cdots |v_{j(i+N)}^k| \cdots |v_{j(2N)}^k|]$, $i = 1, 2, \cdots, N$; $j = 1, 2, \cdots M$; $k = 1, 2, \cdots, G_{\max}$; where k represents generation; C_j^k represents chromosome, i.e. a search path; θ, v represent the direction and velocity of the coding gene; $G_{\max}$ represents the largest generation; j represents the jth individual of the population; i represents the genetic position, i.e. search The ith stage of the path; M represents the population size; N represents the total number of stages of the path.

During the evolution process, two variables v and θ in the same search phase are used together for genetic operations.

4.2. Genetic algorithm strategy

In terms of genetic manipulation, IGA uses improved crossover and mutation operators to guide population evolution. Before discussing in detail, the definitions of some important parameters should be emphasized.

In genetic iteration, the progeny consists of three parts: the elite individual in the parent, the progeny population after the crossover operation, and the progeny population after the mutation operation. In each generation, two genetic operations (crossover and mutation) are performed independently, and the resulting two groups of new individuals and parent elites form a descendant population. The proportion of the elite elites in the population is called the elite individual ratio P_E, and the proportion of the two groups of new individuals in the offspring population is called the crossover probability and the mutation probability, which are recorded as P_C and P_M ($P_E + P_C + P_M = 1$). The definitions of crossover probability and

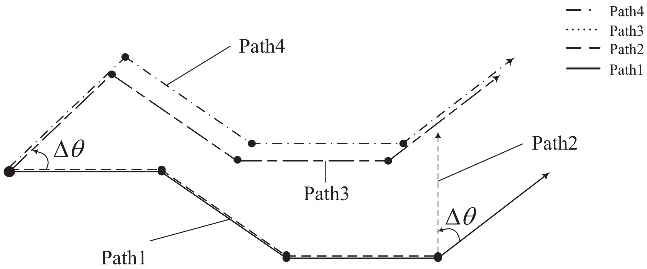

Fig. 3. Effects of direction and velocity on search path in different steps.

mutation probability are not the same as those in other GAs. Through many experiments and parameter comparisons, this paper selects $P_E = 0.01$, $P_C = 0.24$, $P_M = 0.75$.

4.3. Cross operation

The crossover operation uses the roulette method to select individuals with the number of $P_C \times M$ from the parents and obtains new individuals through the two-two crossover, which plays a role in enriching the diversity of the population. The intersection is randomly selected at $1/8 \sim 3/8$ of the chromosome length.

4.4. Improved thinking of mutation operation

The direction and magnitude of the mutation directly affect the efficiency and convergence speed of the algorithm [18]. However, in the general GA variation operation, the gene change often replaces the parent gene by simply generating a random number. Obviously, this variation is too blind, making the algorithm with the convergence rate. The literature [19] uses a novel adaptive mutation strategy to improve the convergence speed of genetic algorithms. In this paper, the mutation operation was improved according to the literature [19]. In the following, according to the characteristics of USV search, the improved measures the mutation operation are analyzed from three aspects:

(1) Use the optimal individual of the father to adaptively control the direction of variation. Since the optimal parent of the father has the highest fitness value during evolution, it is often closest to the global optimal solution in the population. Therefore, this information can be used to control the direction of mutation, so that the individual being manipulated mutates toward the direction of the optimal individual of the father, and guides the evolution of the population. Similar ideas are reflected in the revolving door operation of quantum evolutionary algorithms and the velocity update equations of particle swarm optimization algorithms. However, most of these algorithms select the current optimal individuals to guide the evolution of the population, and this paper selects the optimal individuals of the father. This enhances the global search capabilities of the algorithm.

(2) The amplitude of the variation is adaptively controlled at different stages of the search path. In Fig. 3, path 1 and path 3 are obtained by performing the same variation operation on the path of the different stages. It can be seen from Fig. 3 that the early the step is, the more the direction of search path changes, which means the influence is greater. The path of the first stage of the path 3 is subjected to the same variation operation to obtain the path 4. The effect of speed on the path is small. The difference in the influence of the stage of the variable category and its variation on the path is a key difference between optimal path planning problem and other numerical optimization problems. Therefore, the magnitude of the mutation should be adaptively adjusted according to the type of the variable and the stage in which it is located.

(3) The amplitude of mutation is adaptively controlled according to different evolution stages. The mutation in the early generation helps to increase population diversity, while in the later generation, good individuals gradually approach the optimal solution and should avoid violent variability (such as 180° rotation of the direction). Therefore, the magnitude of mutation should be adaptively reduced with the increase of generation.

4.5. Improved mutation strategy

Based on the above ideas, this paper improves the mutation operation and proposes the following adaptive mutation strategy:

$$\begin{cases} \theta_{ji}^{k} = \theta_{ji}^{k-1} + A_1 \cdot D_1 \cdot \lambda(i) \cdot \delta_1(k) \cdot Rand, \\ v_{j(i+N)}^{k} = v_{j(i+N)}^{k-1} + A_2 \cdot D_2 \cdot \delta_2(k) \cdot Rand, \end{cases}$$
$$i = 1, 2, \cdots, N;\ j = 1, 2, \cdots, M;\ k = 2, \cdots, G_{\max}. \tag{3}$$

Where: θ_{ji}^{k}, $v_{j(i+N)}^{k}$ are the kth generation gene; D is the variation direction control factor; $\lambda(i)$ is the gene position control factor; $\delta(k)$ is the evolutionary generation control factor; *Rand* is the rand number between [0,1]; A is a constant. If the gene value obtained after the mutation of (3) is out of the feasible range, it is adjusted by (4).

$$\theta' = \begin{cases} \theta - 2\pi, \theta > 2\pi \\ \theta + 2\pi, \theta < 0 \\ \theta \end{cases} \qquad v\prime = \begin{cases} v_{\max}, v > v_{\max} \\ v_{\min}, v < v_{\min} \\ v \end{cases} \tag{4}$$

Through a large number of experiments and parameter comparisons, the constant values and control factors selected in this paper are given by (5) to (7). Under these parameters, the algorithm can achieve the best optimization performance and obtain stable operation results.

$$\begin{cases} A_1 = \pi \\ A_2 = \frac{1}{2} \cdot (v_{\max} - v_{\min}) \\ \lambda(i) = \frac{i}{N} \\ \delta_1(k) = \exp\left[-2.7 \cdot (\frac{k}{G_{\max}})\right] \\ \delta_2(k) = \exp\left[-2.5 \cdot (\frac{k}{G_{\max}})\right] \end{cases} \tag{5}$$

In the design of the mutation direction control factor D, acting the guiding role of the optimal individual of the father, make the offspring mutate toward the optimal individual. The father's optimal individual is recorded as $C_B^{k-1} = [|\theta_{B1}^{k-1}| \cdots |\theta_{Bi}^{k-1}| \cdots |\theta_{BN}^{k-1}||v_{B(1+N)}^{k-1}| \cdots |v_{B(i+N)}^{k-1}| \cdots |v_{B(2N)}^{k-1}|]$. The two types of directional control factors D are determined by (6) and (7):

$$D_1 = \begin{cases} 1, \theta_{ji}^{k-1} < \theta_{Bi}^{k-1} \\ -1, \theta_{ji}^{k-1} > \theta_{Bi}^{k-1} \end{cases} \tag{6}$$

$$D_2 = \begin{cases} 1, v_{ji}^{k-1} < v_{Bi}^{k-1} \\ -1, v_{ji}^{k-1} > v_{Bi}^{k-1} \end{cases}. \tag{7}$$

The adaptive mutation direction of the gene obtained by D can make the operating search path continue to approach the optimal path of the parent.

According to the 3-point improvement idea in Section 4.4, IGA introduces three control factors D, λ and δ, and designs an adaptive mutation strategy. It can be seen from Eq. (3) that the direction of the mutation operation is controlled by D, and the amplitude is jointly controlled by other factors.

After introducing the direction control factor D, the algorithm adaptively controls the mutation direction by using the information of the best individual of the father, which accelerates the convergence speed. After introducing the gene position control factor λ, the mutation amplitude increases linearly with the order of the gene position, that is. In the path, the earlier the step is, the smaller the mutation range is. After introducing the generation control factor δ, the mutation range is large in the early stage of evolution, and the solution space can be widely searched to avoid falling into local optimum. In the later stage of evolution, the mutation amplitude is adaptively reduced, and the mutation efficiency is improved by fine-tuning the elite individuals.

5. Simulation

Assuming $T = 0$ h, the emerging submarine target is detected in a certain sea area at the *TS* point, then submerges into the water and escapes from the water surface quickly. The detection information is immediately transmitted to the USV, which rushes to the certain sea area and operates the anti-submarine search. The USV is 5 m long and 2 m wide, but the size of the USV is too small compared to the distance between USV and the target. So the impact of the size of USV on optimal search path planning is not considered in this paper. Based on this background, the target and the searcher are separately described.

The starting coordinates of the known target are $TS = (120\text{n mile}, 120\text{n mile})$, the target speed is assumed as $v_T = 10$ kn, that the target heading θ is uniformly distributed in the range of $[0, 2\pi]$. The mean value μ_{Φ_1} or μ_{Φ_2} of two-dimensional normal noise Φ is 0n mile, standard deviation σ_{Φ_1} or σ_{Φ_2} is 0.2n mile, correlation coefficient ρ_{Φ_1,Φ_2} is 0. The number of simulations of the target path N_T is 10,000.

The USV starts the search at $T = 0$ h, the starting position coordinates is $SS = (100\text{n mile}, 100\text{n mile})$, the given search time is $T_S = 10$ h, and the duration of each stage is $\text{Stept}_s = 0.5$ h, the total number of stages is $N_{\text{Step}} = 20$. The direction of each phase is θ_S is in the range of [0 rad, 2π rad], and the velocity v_S is in the range of [10 kn, 25 kn]. The detection time interval is Δt_D=0.1 h, and the sonar detection formula is as shown in Eq. (1). The CDP of each search path is as in formula (2).

The population is initialized by a simple method: the initial search scheme is a uniform linear motion for the USV, and the path direction is selected at equal intervals within the sector of 60° around the *SS* and *TS* connections. The speed of the initial search path is Randomly selected within [10 kn, 25 kn].

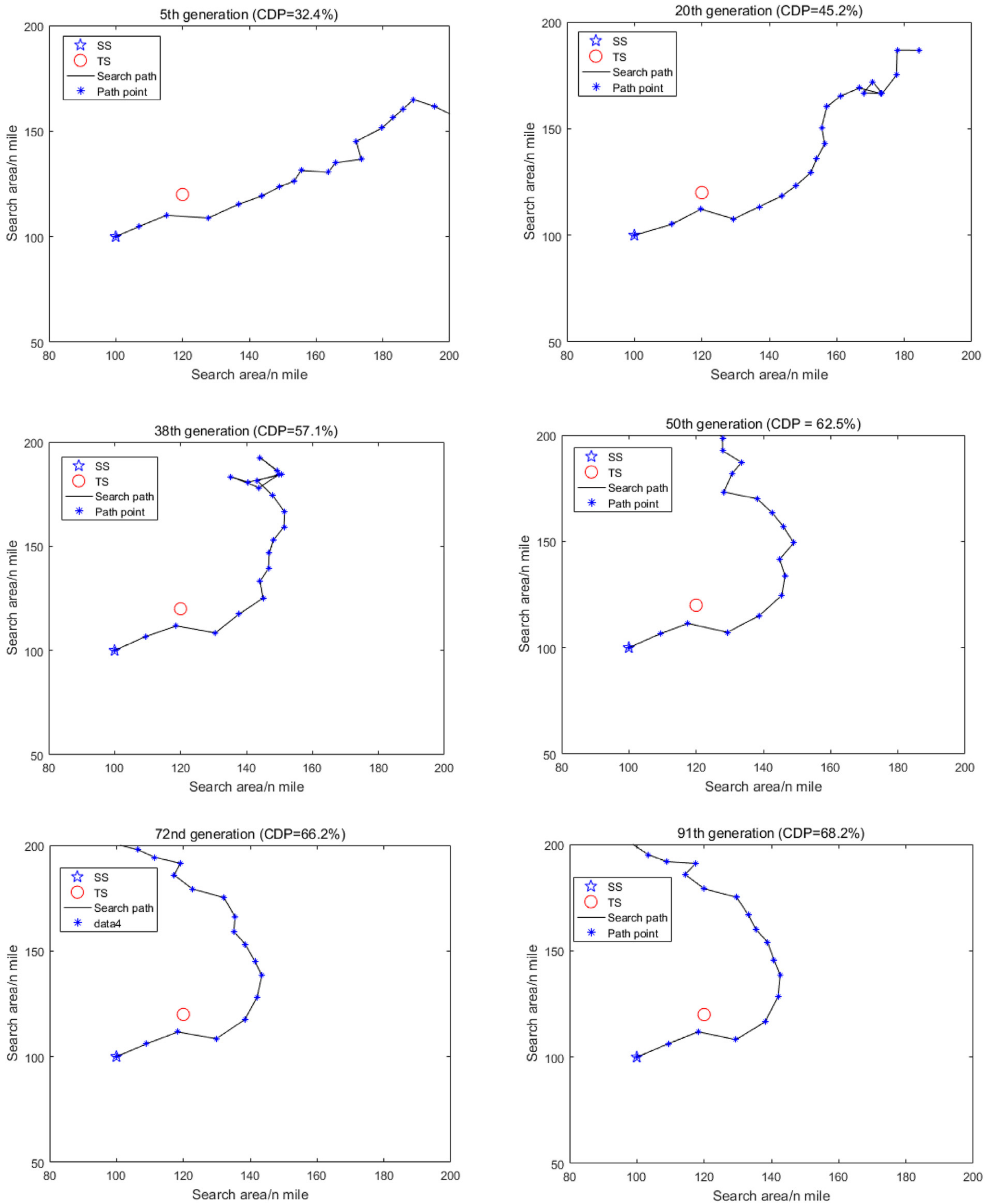

Fig. 4. Optimal search path of selected generation.

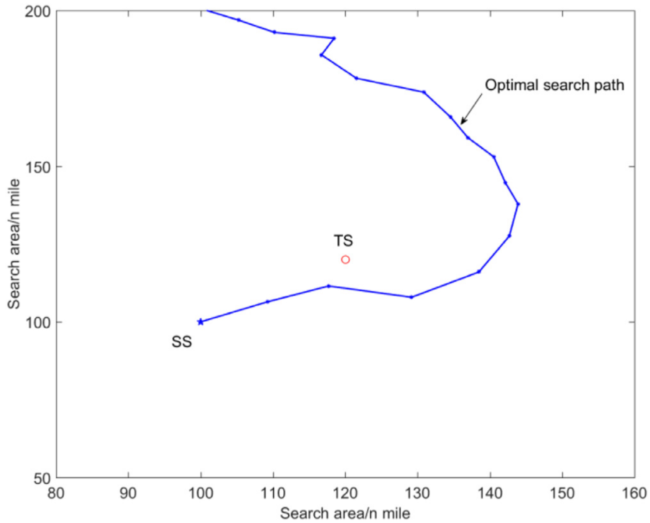

Fig. 5. Optimal search path calculated by IGA.

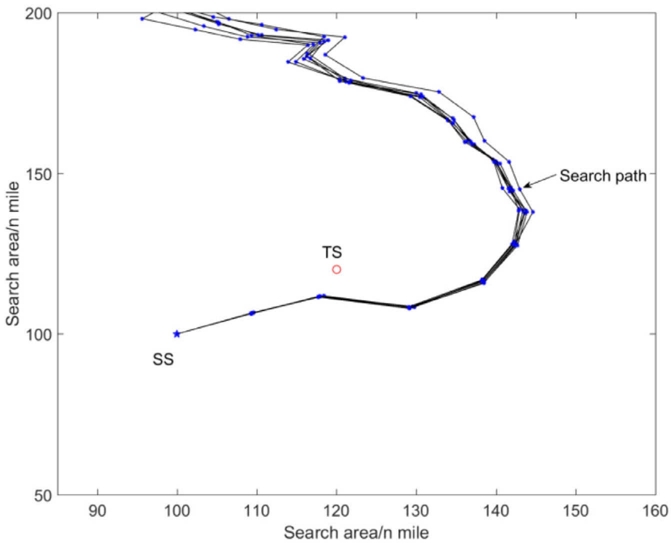

Fig. 6. Seven search paths with high CDP.

The algorithm parameters are set as follows: population size is $M = 100$, chromosome length is $2N = 40$, maximum generation is $G_{\max} = 100$, elite individual ratio $P_E = 0.01$, crossover probability $P_C = 0.\ 24$, mutation probability $P_M = 0.75$. Fig. 4 shows the optimal path search paths with the highest CDP for selected generations. The evolutional process indicates that the IGA performs effectively to increasing the CDP.

As shown in Fig. 5, through 100 independent simulations, the IGA presents the optimal search path for the USV anti-submarine search. The CDP can reach to $F_{\mathrm{CDP}}(10) = 70.6\%$, and the average speed of USV is 19.7 kn The optimal search path for USV anti-submarine search is similar to the logarithmic spiral search curve, which is a suitable search method for searcher with constant search velocity to search escaping target with constant speed.

In order to validate the effectiveness of IGA, the standard GA is selected for comparison. The population initialization method is as the same as the IGA. The maximum genetic iteration is 100, the population size is 100, the crossover probability is 0.3, and the mutation probability is 0.7. The mutation strategy is to randomly mutate within the feasible range. The operation results are shown in Table 1.

The results show that IGA can calculate a search path with higher CDP than a standard genetic algorithm. The average fitness of IGA is approximately equal to the optimal fitness, which is 23% more than the standard genetic algorithm. That indicates that IGA has strong global optimization ability and stability. It takes less time to perform calculations using IGA. It shows that IGA has higher computational efficiency.

Table 1
Result of different algorithms.

Algorithm	Optimal fitness (%)	Average fitness (%)	Calculating time (s)
GA	53.7	44.2	330
IGA	70.6	67.2	224

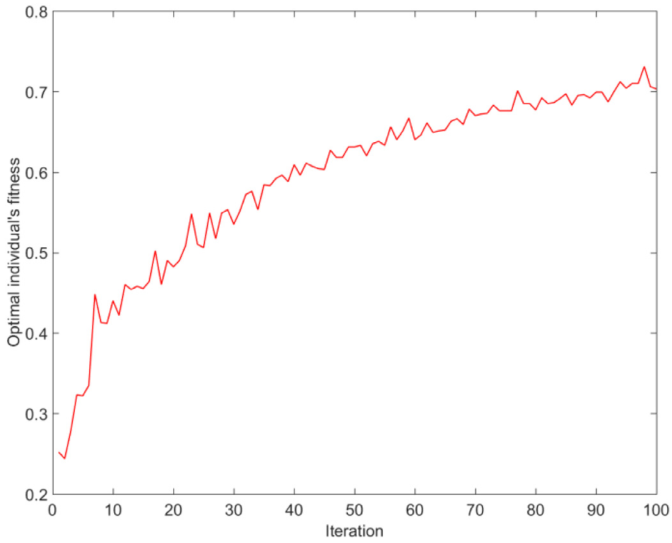

Fig. 7. Optimal fitness evolution curve.

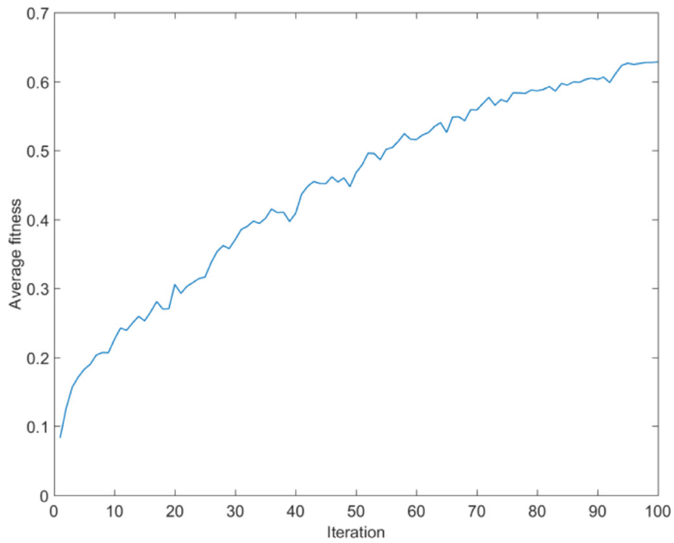

Fig. 8. Average fitness evolution curve.

The cumulative detection probability of the optimal search path shown in Fig. 5 is 70.6%, and the average speed of USV is 19.7 kn

When viewing the results after the simulation experiment, it can be seen that the heading angle of the first 2-3 path stages of USV is small, and the heading angle is basically the connection angle between SS and TS, so that USV can approach the target as quickly as possible, in line with the actual situation of submarine search.

Fig. 6 shows seven search paths of high cumulative detection probability. Their average cumulative detection probability is 68.2%, which is only 2.4% less than the optimal search path, indicating that the IGA has good stability and the resulting path is similarly high, which can be regarded as convergence.

Fig. 7 shows the variation of the optimal fitness of each generation of the population. the figure shows that the optimal fitness is increasing overall and there is local oscillation. The optimal fitness rate is higher in the early stage of evolution and increases to about 40% after 10 iterations. At the end of evolution, the optimal fitness growth rate is low and gradually converges.

Fig. 8 is an evolutionary curve of the average fitness value of the population during the evolution process. It can be seen from the figure that the average fitness value growth trend is relatively flat, and the oscillation amplitude is not as dramatic as shown in Fig. 7. The average fitness of the population is 66.5%, which is only less than 5% compared with the optimal fitness, indicating that the cumulative detection probability of IGA for all search paths of the whole population is greatly improved.

From the above analysis, IGA can improve the convergence speed by introducing three control factors, so that USV can improve the search probability in the early stage and can obtain many efficient search path schemes. However, many data about USV cannot be checked for confidentiality reasons. So it cannot be verified by specific examples.

6. Conclusion

In this paper, an optimal anti-submarine search path model based on an improved genetic algorithm is proposed for unmanned surface vehicles (USV). The speed and direction of the USV can be optimized simultaneously. The improved genetic algorithm can adaptively control the direction and amplitude of the mutation by introducing three dominant factors. The convergence speed and the stability of the proposed algorithm are enhanced. The simulation results indicate that the cumulative detection probability of the optimal search path can reach to 70% under the specified condition. The performance of the improved genetic algorithm is validated by the standard genetic algorithm, and the validation results show that the improved genetic algorithm can perform more effectively and efficiently with strong stability and fast convergence. This research indicates that the optimal path for unmanned surface vehicles is effective and suggestive for anti-submarine search.

Declaration of Competing Interest

None.

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