Path Planning for Unmanned Surface Vehicle based on genetic algorithm and sequential quadratic programming

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***Abstract*—Path planning and obstacle avoidance of Unmanned Surface Vehicle (USV) is one of the hottest research topics in modern national defense and ocean engineering. Considering the issue of obstacle-free path planning of USV, this paper focuses on a 3-DoF USV and develops an algorithm design. We adopt Gauss pseudo-spectral method to discretize control model and make use of a hybrid algorithm to optimize which combines the advantage of genetic algorithm and sequential quadratic programming algorithm. Simulation results show that this method can quickly explore a high-precision route in an unknown environment which meets the mobility requirement of USV without setting the initial value artificially.**

Keywords—Unmanned Surface Vehicle (USV), path planning, genetic algorithm, sequential quadratic programming

I. INTRODUCTION (*HEADING 1*)

Unmanned Surface Vehicle (USV) is a kind of autonomous unmanned equipment. Due to its good flexibility and ability to adapt to harsh environment, it has been used in military fields, especially in wartime, and plays a significant role in anti-submarine and maritime reconnaissance.

Path planning is a key research direction of USV control, which aims for a safe route subject to the vehicle's self-perception to the marine environment. Traditionally, path planning is mainly divided into two types according to environment information. One is global path planning based on the map with a large scope and known target location as shown in Ref. [1], and the other is obstacle-free path planning for unknown obstacles in a small scope as shown in Ref. [2].

A* algorithm and artificial potential field method are commonly used in the path planning of unmanned vehicles. A* algorithm is usually used in combination with the grid map which is used to describe the environment. The smaller the grid is divided, the more accurate is acquired, however, the larger storage space is occupied and the time consumption grows exponentially at the same time. Although the artificial potential field method is simple and good at real-time performance, it has many disadvantages. Such as the path is not smooth enough and the research tends to fall into local optima if a "C" shaped obstacle is encountered. Moreover, it is difficult to take into account the mobility requirement of vehicles and its dynamics constraints in these methods. So, the reliability of the planned path is poor.

The obstacle-free path planning method for USV adopted in this paper is inspired from the field of spacecraft. This method is called pseudo-spectral method which is a kinds of direct method. The advantage of pseudo-spectral method is that it has a large radius of convergence, does not need accurate initial value prediction, does not need to guess the covariant variables, and can obtain a high precision result with a few discrete points. However, when solving such problems the traditional indirect method needs to derive the co-state equation and cross-sectional conditions. Especially in the path planning problem, there are various constraints, which make the indirect method more complex. Therefore, compared with the traditional indirect method, the pseudo-spectral method has more advantages. In Ref. [3], the application of pseudo-spectral method in discretizing model is described, the principle of it is discussed, which can transform the optimal control problem into a nonlinear programming problem in time domain. This method has certain advantages in solving precision and speed. Ref. [4] adopts the Gauss pseudo-spectral method and proposes an improved strategy to complete the path optimization of the aircraft.

Genetic Algorithm (GA) is derived from evolutionary theory and has the advantage of strong global search ability. Meanwhile, it is independent on initial values, so it has been widely used in global path planning. The disadvantages of GA lie in its low running speed and low global search efficiency. In Red. [5], GA and grid method are combined to solve the path planning problem for mobile robots. In Ref. [6], the genetic algorithm is improved to avoid the shortcoming of prematurity and complete the route planning of soccer robot. GA can be combined with gradient algorithm. Sequential quadratic programming (SQP) is a kind of gradient algorithm, which is commonly used to solve large-scale nonlinear programming problems. However, this algorithm is highly dependent on the initial value, with a small convergence radius. According to the characteristics of these two algorithm, the combination of GA and SQP can complement each other's advantages and attain better results. In Ref. [7] and Ref. [8], some scholars have applied GA and SQP to practical problems and achieved good results so far.

In Ref. [9], an autonomous path planning model based on deep reinforcement learning is proposed for path planning of USV. The experiments results show that the model can realize path planning with fast convergence speed autonomously. In Ref. [10], considering the kinematic and dynamic model of

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USV, an online path planning scheme based on asymptotically optimal rapidly extending random tree is proposed. Through experiment, this scheme can realize path planning for USV in the actual marine environment.

In this paper, the obstacle-free path planning of USV for channel surveyed is considered, which also takes into account the underactuated dynamics constraints of the vehicle. Firstly, a time optimal path planning model with obstacle constraints, maneuvering performance constraints and state equation constraints is established. Secondly Gauss pseudo-spectral method is adopted to discretize control model which has high precision. Finally, a hybrid algorithm is used to optimize the discrete model, which combines the global searching ability of GA as well as the local searching ability of SQP. Compared with genetic algorithm alone, this hybrid algorithm is faster and more accurate. The simulation results show that this method can quickly provide a high-precision route which meets the mobility requirements of USV and has high safety reliability.

II. PROBLEM SRATEMENT

A. Mathematical Model of Underactuated USV

First, a brief introduction is given to the commonly used coordinate system for USV, including the inertial coordinate system $O-XYZ$ and ship coordinate system $o-x_b y_b z_b$, which is shown in Fig. 1. O is the origin of inertial coordinate system, OX points to the north, OY points to the east, OZ points to the geocentric direction. In the inertial coordinate system, the displacements in the three directions are denoted as x, y, z. The ship coordinate system takes o as the origin of coordinates, ox_b is the bow direction, oz_b points to the center of the earth, oy_b is the starboard direction of the ship.

The vector of external forces applied to USV can be denoted as $\boldsymbol{F}$, the projections on each coordinate axis of ship coordinate system are X, Y, Z. Similarly, the vector of moment of force applied to USV is denoted as $\boldsymbol{T}$, the projections on each coordinate axis of ship coordinate system respectively are K, M, N.

For the convenience of illustration, the relevant variables of USV are summarized as follows:

$$\begin{aligned}
&\boldsymbol{\eta}=\left[\boldsymbol{\eta}_1,\boldsymbol{\eta}_2\right],\ \boldsymbol{\eta}_1=\left[x,y,z\right]^{\mathrm{T}},\ \boldsymbol{\eta}_2=\left[\phi,\theta,\psi\right]^{\mathrm{T}}\\
&\boldsymbol{\upsilon}=\left[\boldsymbol{\upsilon}_1,\boldsymbol{\upsilon}_2\right],\ \boldsymbol{\upsilon}_1=\left[u,v,w\right]^{\mathrm{T}},\ \boldsymbol{\upsilon}_2=\left[p,q,r\right]^{\mathrm{T}}\\
&\boldsymbol{\tau}=\left[\boldsymbol{F},\boldsymbol{T}\right]\qquad \boldsymbol{F}=\left[X,Y,Z\right]^{\mathrm{T}},\boldsymbol{T}=\left[K,M,N\right]^{\mathrm{T}}
\end{aligned}\tag{1}$$

where $\boldsymbol{\eta}$ is position vector and angle vector of USV in inertial coordinate system, $\boldsymbol{\upsilon}$ is linear velocity vector and angle velocity vector of USV in ship coordinate system, $\boldsymbol{\tau}$ is external forces vector and moment vector applied to USV in ship coordinate system.

In general, the USV has six degrees of freedom in each direction. This paper mainly discusses path planning. In order to facilitate the design, the model is simplified and only three kinds of motions of the USV, namely surge, sway and yaw, are considered. Therefore the following assumptions are made.

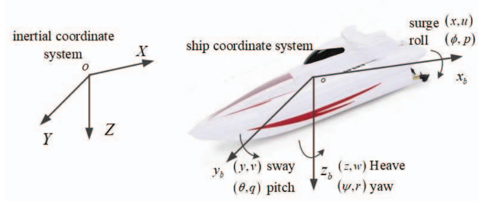

Fig. 1. Reference frame of USV

(1) Ignore the other three degrees of freedom, the velocity and angular velocity is 0. (2) The inertial axis of the USV coincides with the axes of the ship coordinate system. The origin of the ship coordinate system is at the center of gravity of the ship. The mass and density of the ship are evenly distributed, meanwhile, the ship is symmetrical not only front and rear but also right and left.

Accordingly, the USV model with three degree of freedom is simplified to the following form:

$$\begin{gathered}
\dot{\boldsymbol{\eta}}=\boldsymbol{R}(\psi)\boldsymbol{\upsilon}\\
\boldsymbol{M}\dot{\boldsymbol{\upsilon}}+\boldsymbol{C}\left(\boldsymbol{\upsilon}\right)\boldsymbol{\upsilon}+\boldsymbol{D}\left(\boldsymbol{\upsilon}\right)\boldsymbol{\upsilon}=\boldsymbol{\tau}
\end{gathered}\tag{2}$$

where

$$\boldsymbol{R}(\psi)=\begin{bmatrix}\cos\psi & -\sin\psi & 0\\ \sin\psi & \cos\psi & 0\\ 0 & 0 & 1\end{bmatrix},\ \boldsymbol{M}=\begin{bmatrix}m_{11} & 0 & 0\\ 0 & m_{22} & 0\\ 0 & 0 & m_{33}\end{bmatrix}$$

$$\boldsymbol{C}(\boldsymbol{v})=\begin{bmatrix}0 & 0 & C_{13}\\ 0 & 0 & C_{23}\\ -C_{31} & -C_{23} & 0\end{bmatrix},\ \boldsymbol{D}(\boldsymbol{v})=\begin{bmatrix}d_{11} & 0 & 0\\ 0 & d_{22} & 0\\ 0 & 0 & d_{33}\end{bmatrix}$$

$$\begin{aligned}
&m_{11}=m-X_{\dot{u}},\ m_{22}=m-Y_{\dot{v}},\ m_{33}=I_z-N_{\dot{r}}\\
&C_{13}=-m_{22}v,\ C_{23}=m_{11}u\\
&d_{11}=-X_u,d_{22}=-X_v,d_{33}=-N_r
\end{aligned}$$

In Eq. (2), $\boldsymbol{\eta}=\left[x,y,\psi\right]^{\mathrm{T}}$, x is displacement in surge direction, y is displacement in sway direction, ψ is course angle. $\boldsymbol{v}=\left[u,v,r\right]^{\mathrm{T}}$, u is velocity in surge direction, v is velocity in sway direction, r is course angular velocity. $\boldsymbol{\tau}=\left[T_u\ 0\ T_r\right]^{\mathrm{T}}$, T_u is longitudinal thrust, T_r is yaw force provided by rudder. $\boldsymbol{R}(\psi)$, $\boldsymbol{M}$, $\boldsymbol{C}\left(\boldsymbol{v}\right)$ and $\boldsymbol{D}\left(\boldsymbol{v}\right)$ are all constant matrices. More information about this model can be seen in Ref. [11].

B. Obstacle-free path planning model

For unmanned vehicles that are completing the task of channel survey, it is of great importance to timely adjust their state, quickly avoid obstacles and return to the original working state after encountering obstacles. Therefore, we set up a time-optimal obstacle avoidance path planning model based on this background.

The obstacle-free path planning problem can be generally described as: search for control variables which makes performance indicators to a minimum, meanwhile, equation of state constraints, process constraints brought by maneuverability and obstacles, boundary constraints at the initial and final moments are all satisfied.

The performance indicators for this problem and the constraints that the USV needs to meet are as follows:

1) In this paper, the shortest running time is taken as the performance indicators for path planning of USV. So it can be expressed as follows

$$J = \int_{t_0}^{t_f} 1\, dt \tag{3}$$

2) Eq. (2) can be taken as the state constraints for the USV.

3) The speed in every directions, course angle, propulsive force and yaw force of USV are finite, that is, state variables and control variables should meet the following inequality constraints:

$$|u| \le u_{\max}, |v| \le v_{\max}, |r| \le r_{\max}, |\psi| \le \psi_{\max} \tag{4}$$

$$|T_u| \le T_{u\max}, |T_r| \le T_{r\max} \tag{5}$$

where $u_{\max}$, $v_{\max}$, $r_{\max}$, $\psi_{\max}$, $T_{u\max}$, $T_{r\max}$ are all nonnegative constants.

4) As for the restricted navigation zone constraints, obstacles can be divided into two categories according to different working environments: static obstacles and dynamic obstacles. The USV should keep a safe distance from obstacles during navigation. For the convenience of description, the obstacle is taken as a circular area and the radius of the circle is R_j , $j = 1,2,\ldots j_N$, j_N is the number of obstacles. Static obstacles can be regarded as special dynamic obstacles which V_j and ψ_j are 0. Therefore, the states of the two kinds of obstacles at a certain time can be uniformly described as:

$$\begin{cases} x_j(t) = x_{j0} + V_j \cos(\psi_j)t \\ y_j(t) = y_{j0} + V_j \sin(\psi_j)t \end{cases} \tag{6}$$

where (x_{j0}, y_{j0}) is the initial state, V_j is the speed and ψ_j is the course angle of the obstacle.

Therefore, the obstacle constraint can be uniformly described as:

$$S_j(t) = (x(t) - x_j(t))^2 + (\mathrm{y}(t) - y_j(t))^2 - R_j^2 \ge l \tag{7}$$

where $j = 1,2,\ldots j_N$, l is safe distance from USV to the obstacles.

5) As for boundary condition constraints, the USV state noted as $\boldsymbol{x}(t_0)$ is usually determined at the starting point when $t_0 = 0$, and the time to the end is denoted as t_f . At this time, the USV state is set as $\boldsymbol{x}(t_f)$ .Therefore, it meets:

$$\boldsymbol{x}(t_0) = \boldsymbol{x}_0, \boldsymbol{x}(t_f) = \boldsymbol{x}_f \tag{8}$$

III. Methodology

A. Gauss pseudo-spectral method

The Gaussian pseudo-spectral method is used to transform the time-optimal control model into a medium or large scale nonlinear programming problem. This method is widely used because of its high precision and calculation efficiency. In Ref.[12] and Ref. [13], the principle of Gauss pseudo-spectral method is explained in details.

After discretization we can get the following results:

The dynamic differential equation can be written as the following form:

$$\sum_{i=0}^{N} D_{ki}\boldsymbol{X}(\tau_i) - \frac{t_f - t_0}{2}\boldsymbol{f}(\boldsymbol{X}(\tau_k), \boldsymbol{U}(\tau_k), \tau_k; t_0, t_f) = 0 \tag{9}$$

where $k = 1,\ldots,N$.

Where $\boldsymbol{D}$ is a differential matrix. $\boldsymbol{X}(\tau)$ and $\boldsymbol{U}(\tau)$, respectively, are state variable and control variable after the discretization. They can be calculated as follows:

$$D_{ki} = \dot{L}_i(\tau_k) = \begin{cases} \dfrac{\dot{b}(\tau_k)}{\dot{b}(\tau_k)(\tau_k - \tau_i)}, & k \ne i \\ \dfrac{\ddot{b}(\tau_k)}{2\dot{b}(\tau_k)}, & k = i \end{cases} \tag{10}$$

$$\boldsymbol{x}(\tau) \approx \boldsymbol{X}(\tau) = \sum_{i=0}^{N} L_i(\tau)\boldsymbol{X}(\tau_i) \tag{11}$$

$$L_i(\tau) = \prod_{j=0, j\ne i}^{N} \frac{\tau - \tau_j}{\tau_i - \tau_j} \tag{12}$$

$$\boldsymbol{u}(\tau) \approx \boldsymbol{U}(\tau) = \sum_{i=1}^{N} \tilde{L}_i(\tau)\boldsymbol{U}(\tau_i) \tag{13}$$

$$\tilde{L}_i(\tau) = \prod_{j=1, j\ne i}^{N} \frac{\tau - \tau_j}{\tau_i - \tau_j} \tag{14}$$

where $b(\tau) = \prod_{i=0}^{N}(\tau - \tau_i)$, τ_{i} is the zero of Legendre polynomial, which is called Legendre-Gauss (LG) point.

In this problem, there is a constraint on the terminal state, which can be expressed as the following form:

$$\boldsymbol{X}(\tau_f) = \boldsymbol{X}(\tau_0) - \frac{\tau_f - \tau_0}{2}\sum_{k=1}^{N} \omega_k \boldsymbol{f}(\boldsymbol{X}(\tau_k), \boldsymbol{U}(\tau_k), \tau_k; t_0, t_f) \tag{15}$$

where w_k is the weight of Gauss integration, which can be written as:

$$w_k = \frac{2}{(1 - \tau_k{}^2)[\dot{P}_N(\tau_k)]^2} \qquad (k = 1,\ldots,N) \tag{16}$$

where $P_N(\tau)$ is Legendre polynomial.

According to Gauss integral formula, the performance indicators (3) is rewritten as:

$$\begin{aligned} J = {} & \Phi\left(\boldsymbol{X}(-1), t_0, \boldsymbol{X}(1), t_f\right) \\ & + \frac{t_f - f_0}{2}\sum_{k=1}^{N} \omega_k g(\boldsymbol{X}(\tau_k), \boldsymbol{U}(\tau_k), \tau_k, t_0, t_f) \end{aligned} \tag{17}$$

Process constraints, including obstacle constraints and maneuvering performance constraints, can be expressed as:

$$\boldsymbol{C}(\boldsymbol{X}(\tau_k), \boldsymbol{U}(\tau_k), \tau_k, t_0, t_f) \le 0, \ K = 1,\ldots,N \tag{18}$$

So far, the optimal control problem about the path planning, has been transformed into a nonlinear programming problem by the Gauss pseudo-spectral method. For the nonlinear programming problem, the optimization algorithm in the following part will be adopted to solve the problem.

B. Optimization algorithm

A new hybrid optimization algorithm adopted in this paper, not only has the strong global searching ability of GA, but also has the fast convergence speed of SQP. It can greatly improves the computational efficiency. This hybrid optimization can be simply noted as generic algorithm-sequential quadratic programming (GA-SQP). The GA-SQP in USV obstacle-free path planning is introduced as follows:

Flow chart of GA-SQP is shown in Fig. 2. The basic idea of GA-SQP is as follows: First, the GA is used for global search, and the precision requirement, population number and upper limit of iterations of GA don't need to be set too high. The population number and iteration times of GA-SQP are less than that required by GA alone. Thus, near-optimal solutions can be obtained. Then, the obtained results by GA are taken as the initial values of SQP. A local search is operated based on this and the global optimal solution will be obtained quickly.

The steps of GA-SQP are as follows:

1) Select a proper number of LG points according to the simulation environment. More LG points leads to the larger computational consumption. However, if the number of LG points is too few, the path planned will be inaccurate.

2) Set parameters for GA, such as population size, maximum number of iterations. Code individual genes and initialization of the population. The population size is the number of individuals. The larger the population size is, the more likely the global optimal solution will be obtained. Meanwhile the complexity of the algorithm will increase.

3) Calculate individual fitness function. In the problem of path planning for USV in this paper, the fitness function can be taken as (17).

4) Determine if the termination condition of GA is met. If the condition is satisfied, go to step 7, else go to step 3.

5) Select good genes. Roulette selection method and elite selection strategy are commonly used. The individuals with high fitness in the current population are copied directly into the next generation. The selection probability of the roulette method is as follows:

$$P(x_i) = \frac{f(x_i)}{\sum_{i=1}^{N} f(x_i)} \tag{19}$$

where $f(x_i)$ is the fitness value of individual in the population. N is the population size.

6) Cross and mutate genes. Single point crossing and multi point crossing are common ways of crossing. Variation is a low-probability event, however, it enriches the genetic diversity in a population, which helps to get the optimal solution.

7) Give the results calculated by GA to SQP as initial values. Set parameters for SQP, such as maximum number of iterations, accuracy of calculation or other termination condition.

8) Construct Lagrange multiplier function. The Lagrange function of this nonlinear programming problem can be expressed as:

$$L(\boldsymbol{x},\lambda,\mu) = f(\boldsymbol{x}) + \sum_{i=1}^{m} \lambda_i h_i(\boldsymbol{x}) + \sum_{j=m+1}^{n} \mu_j g_j(\boldsymbol{x}) \tag{20}$$

where λ_i and μ_j are Lagrange multipliers. $h_i(\boldsymbol{x})$ and $g_i(\boldsymbol{x})$ are equality and inequality constraints.

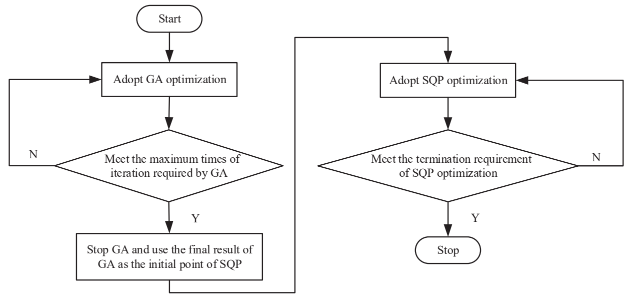

Fig. 2. Flow chart of GA-SQP

9) Calculate the main search direction $\boldsymbol{d}$, step size a_k correction matrix $\boldsymbol{H}_k$ and the value of Lagrange function. Basic structure of SQP includes primary iteration and secondary iteration. The primary iteration converges to the optimal solution of the problem. In the main iteration, the search direction of the next main iteration is determined by quadratic programming. The step size a_k is determined by the golden section linear search. Search direction $\boldsymbol{d}$ can be calculated as follows:

$$\begin{aligned} &\min \quad 0.5\boldsymbol{d}^T \boldsymbol{H}_k \boldsymbol{d} + (\nabla f(\boldsymbol{x}_k))^T \boldsymbol{d} \\ &s.t. \quad (\nabla h_i(\boldsymbol{x}))^T \boldsymbol{d} + h_i(\boldsymbol{x}) = 0 \\ &\qquad\ (\nabla g_i(\boldsymbol{x}))^T \boldsymbol{d} + g_i(\boldsymbol{x}) = 0 \end{aligned} \tag{21}$$

where $\boldsymbol{H}_k$ is a correction matrix and can be expressed as:

$$\boldsymbol{H}_{k+1} = \boldsymbol{H}_k - \frac{\boldsymbol{H}_k \boldsymbol{y}_k \boldsymbol{y}_k^T \boldsymbol{H}_k}{\boldsymbol{y}_k^T \boldsymbol{H}_k \boldsymbol{y}_k} + \frac{\boldsymbol{s}_k \boldsymbol{s}_k^T}{\boldsymbol{y}_k^T \boldsymbol{s}_k} \tag{22}$$

where $\boldsymbol{s}_k = \boldsymbol{x}_{k+1} - \boldsymbol{x}_k$, $\boldsymbol{y}_k = \boldsymbol{G}_{k+1} - \boldsymbol{G}_k$, $\boldsymbol{G}_k$ is the equation for search is the first derivative of the Lagrange function.

10) Determine if the termination condition of SQP is met. If the condition is satisfied, output the result, else go to step 9.

IV. SIMULATION ANALYSIS AND DISCUSSION

In this section, the USV simulation environment is set up. By using the relevant parameters of the experimental ship in Ref. [14], we simulated and verified the effectiveness of the path planning strategy adopted in this paper. Meanwhile, compared with the single use of GA, the advantage of GA-SQP is shown intuitively.

A. Simulation sets

The maneuvering performance parameters of the USV are as follows:

$$\begin{gathered} 0 \le u \le 10 \text{ m/s} \quad |v| \le 5 \text{ m/s} \quad |\psi| \le 180^\circ \\ |T_u| \le 100 \text{ m} \quad |T_r| \le 20 \text{ N} \cdot \text{m} \end{gathered} \tag{23}$$

The initial time is set as $t_0 = 0$ s. The initial and final state constraints are as follows:

$$\begin{aligned} \boldsymbol{x}(t_0) &= \left[0\text{ m},\ 0\text{ m},\ 0^\circ,\ 0.5\text{ m/s},\ 0\text{ m/s},\ 0\text{ rad/s}\right] \\ \boldsymbol{x}(t_f) &= \left[40\text{ m},\ 0\text{ m},\ 0^\circ,\ 0.5\text{ m/s},\ 0\text{ m/s},\ 0\text{ rad/s}\right] \end{aligned} \tag{24}$$

The obstacles are selected as two circular obstacles, one is static obstacle and the other is dynamic. The position of the static obstacle is $(x_{10}, y_{10}) = (10\text{ m},\ 0\text{ m})$ and the radius of it is $R_1 = 4$ m.

The parameters of the dynamic obstacle are as follows:

$$\begin{aligned} (x_{20}, y_{20}) = (36\text{ m},\ 0\text{ m}), \quad R_2 = 2\text{ m} \\ \psi = -180^\circ, \quad V = -1.5\text{ m/s} \end{aligned} \tag{25}$$

To ensure security, a safe distance is set as 1m from USV to the obstacles. So constraints brought by obstacles are as follows:

$$\begin{aligned} &S_1(t) = (x(t) - x_{10})^2 + (y(t) - y_{10})^2 - R_1^2 \\ &S_2(t) = (x(t) - x_{20}(t))^2 + (y(t) - y_{20}(t))^2 - R_2^2 \\ &S_1(t) \geq 1\text{ m}, \quad S_2(t) \geq 1\text{ m} \end{aligned} \tag{26}$$

B. GA-SQP simulation analysis

The purpose of algorithm optimization is to avoid obstacles with the fastest speed, return to the original course, and continue sailing according to the original operating state, so the fitness function can be taken as (17).

First the population size is set as 100, the upper limit of iterations is set as 40, the crossover probability is selected as 0.8, the variation probability is set as 0.2. If the change of fitness value is less than 0.01 and the variation tolerance of the constrained part is less than 0.01, the iteration stops. Then the expected variation tolerance of the objective function and the variation tolerance of the constrained part are both less than 0.01. The actual number of iterations is 100, and the result flag is given and all constraints have been met.

When genetic algorithm is used alone, more iterations are needed, so the upper limit of iteration is higher. The other parameters of them are similar. The comparison of parameters and results of the two methods is shown in Table I.

Simulation results about the path planned for USV are shown in Fig. 3 and Fig. 4, which are optimized by GA-SQP and GA respectively. The annotation about Fig. 3 and Fig. 4 is similar. Static obstacles are represented by black solid circles and dynamic obstacles are represented by dashed hollow circles. A series of hollow circles constitute the path of the dynamic obstacle. t_0 is the start time and t_f is the finish time. t_l is the moment when USV and the dynamic obstacle are closest to each other.

From Table I, Fig. 3 and Fig. 4, the analysis is as follows:

Firstly, the optimal time consumption of GA-SQP is 11.35 seconds, while the value of GA algorithm is 12.27 seconds, which is closer to the global optimal solution. The time is reduced by 0.92 seconds, or about 7.5%.

Secondly, the path planned by GA has a slight horns, while the path planned by GA-SQP is more smooth and closer to the obstacle. Meanwhile, in the second half, the curve is more lower.

TABLE I. COMPARISON BETWEEN GA-SQP AND GA

Aspect of contrast	Comparative data	
Optimization algorithm	GA	GA-SQP
population size of GA	100	100
Iteration times of GA	200	40
Iteration times of SQP	0	100
Constraint tolerance accuracy	Nearly 0.1(not meet expections)	0.01(meet expections)
Optimization result	12.27s	11.35s

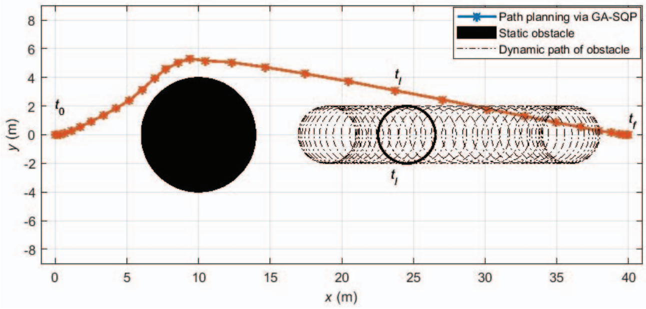

Fig. 3. Path planning based on GA-SQP

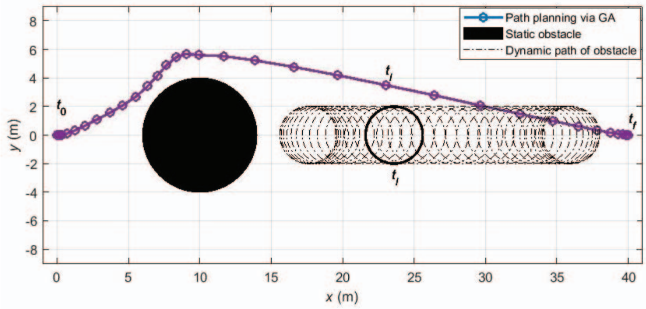

Fig. 4. Path planning based on GA

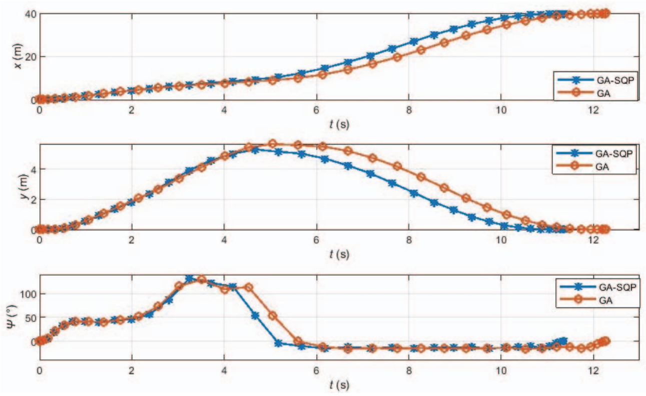

Fig. 5. Curve of surge displacement, sway displacement and course angle

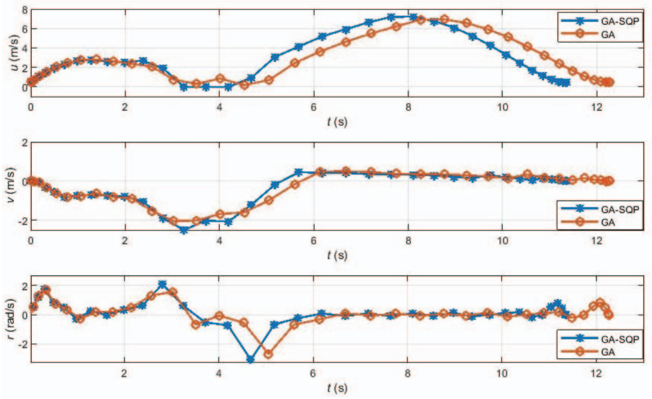

Fig. 6. Curve of velocity in the direction of surge, sway and course angle

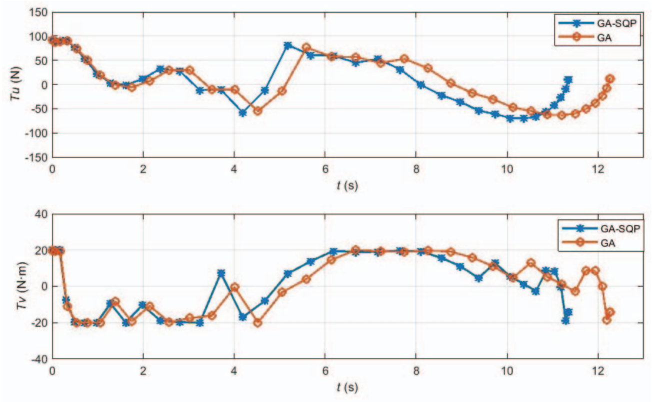

Fig. 7. Curve of forward thrust and yawing moment

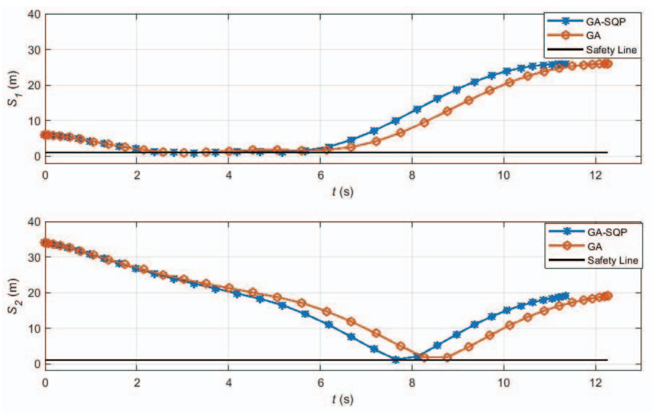

Fig. 8. Curve of distances between USV and obstacles

It can be found from Fig. (5)-(8):

Firstly, the two control variables vary greatly with a sharp fluctuation range, so that the acceleration is relatively large and the optimization goal with the shortest time is met. Secondly, the change curves of state variables all change continuously without any jump, and the initial and final state constraints are satisfied. At last, The distance between USV and obstacles is above the safe distance line from beginning to end. So the security is guaranteed.

V. CONCLUSION

In this paper, an obstacle-free path planning algorithm is designed based on Gauss pseudo-spectral method and GA-SQP algorithm considering the actual background of USV for hydrographic surveying. Taking the shortest running time as the optimization goal, this algorithm comprehensively considers the USV maneuvering performance, starting and ending states, obstacles and other constraints, and plans an obstacle-free path which is suitable for USV. Simulation results show that the design is reasonable and efficient.

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