

# A Model Predictive Adaptive Control Algorithm for Human Occupied Vehicle\*

Wenyang Gan, Wen Pang and Daqi Zhu

*Shanghai Engineering Research Center of Intelligent  
Maritime Search & Rescue and Underwater Vehicles*

*Shanghai Maritime University*

*Haigang Avenue 1550, Shanghai, 201306, China*

zdq367@aliyun.com

**Abstract** - In order to solve the trajectory tracking problem of underwater submersible in the ocean current environment, a model predictive adaptive control method is proposed. The proposed control strategy is mainly composed of two parts: model predictive control and adaptive control. Model predictive control can add kinematic constraints (speed and speed increment constraints) to the controller to obtain the relative desired speed, which is the position tracking system. Because of its ability to change the parameters with the environment, adaptive control is very suitable for the dynamic control of underwater submersible in the ocean current environment, which is the speed tracking control system. Then the whole trajectory tracking process is completed. Lastly, the proposed control strategy is applied to the Deep-sea Warrior human occupied vehicle to verify the tracking effectiveness of it in the ocean current environment.

**Index Terms** - trajectory tracking control, ocean current, adaptive control, model predictive control, human occupied vehicle

## I. INTRODUCTION

With the increasing demand for marine resources in the world, as well as the increasing activity of ocean-related undertakings and maritime rescue missions, underwater submersible [1-2] as a powerful tool to explore the ocean, scientists all over the world have carried out studies on this in order to enhance the marine strength of their countries. Underwater submersible is a new research field, and its research direction is diversified. The main technologies need to conquer are: submarine environment perception, path planning, trajectory tracking and so on. As the core technology, trajectory tracking has been developed rapidly. At present, the main trajectory tracking methods of underwater submersible are PID control [3], fuzzy control [4], backstepping control [5], neural network control [6], sliding mode control [7], adaptive control [8] and so on. These control methods have their own advantages and disadvantages, and scholars have also made various simulation experiments on these methods. For example, the design of PID control is relatively simple, and many years of industrial experience make designers have rich experience in tuning its parameters, but its control performance in dealing with multi-input/output

or nonlinear systems is far from meeting the requirements [9]. The design of fuzzy control does not need the accurate mathematical model of the controlled object, it is to blur the controlled object, after the treatment of fuzzy rules, and then defuzzify to obtain the required control quantity. The establishment of fuzzy rules depends on the subjective consciousness of human beings, which makes fuzzy control subjective and arbitrary [10]. The control law of backstepping control is obtained by backstepping design, which is easy to prove its stability by using Lyapunov theory, but its system order directly affects the complexity of the design. In addition, the problems of speed jump and driving saturation are easy to occur in the control process [11]. Neural network control can fit any complex control system, but it needs a lot of samples to train parameters in order to achieve better control effect, and its real-time performance is not very good [12]. Sliding mode control does not need the accurate model of the controlled object, and has strong robustness to disturbance, but the biggest problem lies in the chattering problem when switching, and the serious chattering problem may destroy the control system [13]. Adaptive control can adapt to process control in a variety of environments because its control parameters can change with the change of control input, but its design process is complex [14]. For some problems existing in the above control methods, many scholars also put forward a variety of improved methods in view of the respective limitations of these control methods.

However, with the higher and higher performance requirements of underwater submersible, the control system of it is becoming more and more complex, which poses a great challenge to the control method. A single control method cannot meet the increasing requirements of control performance, so scholars are also pursuing the combination of a variety of control methods to learn from each other. For example, adaptive control or neural network control is used to formulate fuzzy rules in fuzzy control to reduce the subjective arbitrariness; neural network control is used to improve the speed jump problem of backstepping control; fuzzy control is used to adjust PID parameters and so on.

On the basis of the above description, aiming at the trajectory tracking problem of underwater submersible in the ocean current environment, a double negative feedback closed-loop control system is proposed in this paper. The closed-loop control system includes a position tracking system designed by

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model predictive control and a speed tracking system designed by adaptive control. The organization of this paper is as follows: in Section 2, the kinematic and dynamic equations of underwater submersible are given, which lays the foundation for subsequent control. Model predictive adaptive control strategy is given, and the structure and principle of the whole control system are described; in Section 3, the proposed control strategy is applied to the Deep-sea Warrior HOV to verify the effectiveness; in Section 4, the summary of this paper is given.

## II. MODEL PREDICTIVE ADAPTIVE CONTROL STRATEGY

The six degree-of-freedom (6DOF) kinematic and dynamic equations of underwater submersible are as follows [15]:

$$(M_{RB} + M_A)\dot{\mathbf{v}} + (C_{RB}(\mathbf{v}) + C_A(\mathbf{v}))\mathbf{v} + D(\mathbf{v})\mathbf{v} + \mathbf{g}(\boldsymbol{\eta}) = \mathbf{B}\boldsymbol{\tau} \quad (1)$$

$$\dot{\boldsymbol{\eta}} = \mathbf{J}(\boldsymbol{\eta})\mathbf{v} \quad (2)$$

The control block diagram is shown in Fig. 1. The model predictive adaptive control strategy consists of two parts: the kinematic controller designed by the model predictive control (position tracking control, shown in Fig. 2) and the dynamic controller designed by the adaptive control (speed tracking control, shown in Fig. 3).

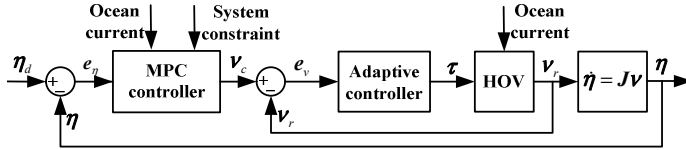


Fig. 1 The control block diagram of MPC adaptive control with the current

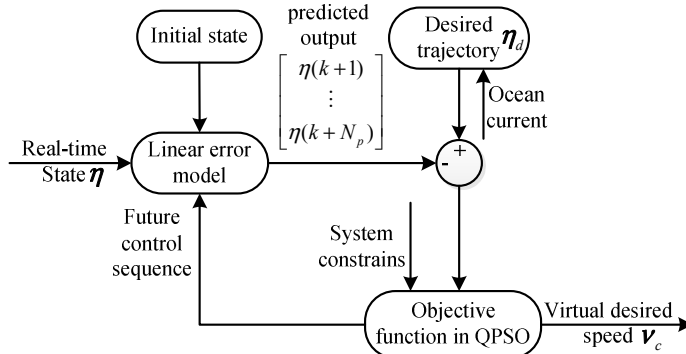


Fig. 2 The block diagram of QPSO-MPC kinematic controller

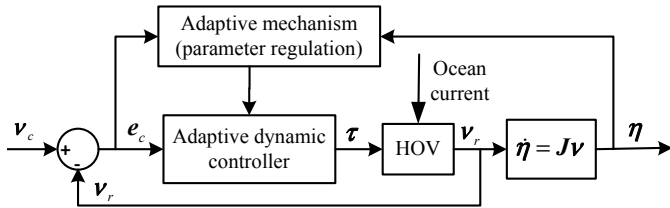


Fig. 3 Adaptive dynamic control

For some underwater submersibles, pitching and rolling are not expected, so the tracking control under four degrees of freedom is studied in this paper. The kinematic model predictive control considering the ocean current information is introduced below. In the model predictive control (MPC), the

first thing to know is the reference trajectory information. So after considering the ocean current information, the reference speed should be the relative reference speed relative to the ocean current. It is assumed that the reference trajectory is  $\boldsymbol{\eta}_d = [x_d \ y_d \ z_d \ \psi_d]^T$ , the reference speed is

$\mathbf{v}_d = [u_d \ v_d \ w_d \ r_d]^T$ , and the ocean current in the inertial coordinate system is  $\mathbf{v}_E = [u_x \ u_y \ w_z \ 0 \ 0 \ 0]^T$ . Then it

can be further obtained that the ocean current in the body-fixed coordinate system is as follows:  $u_u = u_x \cos \psi + u_y \sin \psi$ ,  $v_v = -u_x \sin \psi + u_y \cos \psi$ ,  $w_w = w_z$ .  $u_u, v_v, w_w$  are the currents at surge direction, sway direction, heave direction. So the relative reference speed in the ocean current environment is

$u_d' = u_d - u_u$ ,  $v_d' = v_d - v_v$ ,  $w_d' = w_d - w_w$ ,  $r_d' = r_d$ . On the basis of reference trajectory information and kinematic equation, the linear error model can be obtained as follows:

$$\begin{aligned} \dot{\tilde{\boldsymbol{\eta}}} &= \dot{\boldsymbol{\eta}} - \dot{\boldsymbol{\eta}}_d = \mathbf{J}(\boldsymbol{\eta}_d)\mathbf{v}_d' + \left. \frac{\partial \mathbf{J}(\boldsymbol{\eta})\mathbf{v}}{\partial \boldsymbol{\eta}} \right|_{\boldsymbol{\eta}=\boldsymbol{\eta}_d, \mathbf{v}=\mathbf{v}_d} (\boldsymbol{\eta} - \boldsymbol{\eta}_d) \\ &\quad + \left. \frac{\partial \mathbf{J}(\boldsymbol{\eta})\mathbf{v}}{\partial \mathbf{v}} \right|_{\boldsymbol{\eta}=\boldsymbol{\eta}_d, \mathbf{v}=\mathbf{v}_d} (\mathbf{v} - \mathbf{v}_d') - \mathbf{J}(\boldsymbol{\eta}_d)\mathbf{v}_d' \\ &= \begin{bmatrix} 0 & 0 & 0 & -u_d \sin \psi_d - v_d \sin \psi_d \\ 0 & 0 & 0 & u_d \cos \psi_d - v_d \cos \psi_d \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x - x_d \\ y - y_d \\ z - z_d \\ \psi - \psi_d \end{bmatrix} \\ &\quad + \begin{bmatrix} \cos \psi_d & -\sin \psi_d & 0 & 0 \\ \sin \psi_d & \cos \psi_d & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u - u_d' \\ v - v_d' \\ w - w_d' \\ r - r_d' \end{bmatrix} \end{aligned} \quad (3)$$

Then it is discretized and the linear error model which can be applied to MPC controller is obtained as follows:

$$\tilde{\boldsymbol{\eta}}(k+1) = \mathbf{a}_{k,t} \tilde{\boldsymbol{\eta}}(k) + \mathbf{b}_{k,t} \tilde{\mathbf{v}}(k) \quad (4)$$

$$\text{where } \mathbf{a}_{k,t} = \begin{bmatrix} 1 & 0 & 0 & (-u_d \sin \psi_d - v_d \sin \psi_d)T \\ 0 & 1 & 0 & (u_d \cos \psi_d - v_d \cos \psi_d)T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{b}_{k,t} = \begin{bmatrix} T \cos \psi_d & -T \sin \psi_d & 0 & 0 \\ T \sin \psi_d & T \cos \psi_d & 0 & 0 \\ 0 & 0 & T & 0 \\ 0 & 0 & 0 & T \end{bmatrix}, \text{ T is the sampling time.}$$

At a certain control time, the actual position of the previous moment has been obtained through the last control effect. So the position error between the actual position and the corresponding reference position at the previous time and control quantity (speed) are added to the objective function as the optimization index. However, in a complex control system such as underwater submersible, it is not enough to take the control quantity as the optimization index. Due to the

subsequent dynamic control needs to control the thrust within a certain range, it is necessary to add the control increment, that is the velocity increment, instead of the control quantity to the objective function as the optimization index in the kinematics. The form of the objective function is as follows:

$$F(k) = \sum_{i=1}^{N_p} \|\eta(k+i|t) - \eta_d(k+i|t)\|_Q^2 + \sum_{i=1}^{N_c-1} \|\Delta v(k+i|t)\|_R^2 \quad (5)$$

where  $Q$  and  $R$  are weight matrices. In the underwater submersible control system, there are some constraints in kinematic control, such as the following speed constraints and speed increment constraints:

$$\begin{cases} \mathbf{v}_{\min}(t+k) \leq \mathbf{v}(t+k) \leq \mathbf{v}_{\max}(t+k) \\ \Delta \mathbf{v}_{\min}(t+k) \leq \Delta \mathbf{v}(t+k) \leq \Delta \mathbf{v}_{\max}(t+k) \end{cases} \quad k=0,1,\dots,N_c-1 \quad (6)$$

Convert the above objective function into the following quadratic programming form:

$$\min_{\Delta V(t)} \Delta V(t)^T H_t \Delta V(t) + f_t^T \Delta V(t) \quad (7)$$

where  $H_t = \Phi_t^T Q \Phi_t + R$ ,  $f_t = \Phi_t^T Q \Delta \eta(t)$ ,  $A_t = \begin{bmatrix} \mathbf{a}_{k,t}^{N_c} \\ \vdots \\ \mathbf{a}_{k,t}^{N_p} \end{bmatrix}$ ,

$$\Phi_t = \begin{bmatrix} \mathbf{b}_{k,t} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{a}_{k,t} \mathbf{b}_{k,t} & \mathbf{b}_{k,t} & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{a}_{k,t}^{N_c} \mathbf{b}_{k,t} & \mathbf{a}_{k,t}^{N_c-1} \mathbf{b}_{k,t} & \dots & \mathbf{a}_{k,t} \mathbf{b}_{k,t} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{a}_{k,t}^{N_p-1} \mathbf{b}_{k,t} & \mathbf{a}_{k,t}^{N_p-2} \mathbf{b}_{k,t} & \dots & \mathbf{a}_{k,t}^{N_p-N_c-1} \mathbf{b}_{k,t} \end{bmatrix}. \quad \text{The QPSO}$$

optimization algorithm is used to solve the above quadratic minimizing objective function. After a series of optimization processes, the global optimal solution  $\Delta V_t^* = [\Delta v_t^*, \Delta v_{t+1}^*, \dots, \Delta v_{t+N_c-1}^*]^T$  is obtained. According to the principle of MPC, the first element is returned to the kinematic controller system, that is the relative virtual desired speed  $\mathbf{v}_c = \Delta \mathbf{v}_t^* + \mathbf{v}_d$ .

The adaptive dynamic controller is designed according to the error  $\mathbf{e}_c = \mathbf{v}_c - \mathbf{v}_r$  between the relative virtual expected velocity and the actual velocity of the underwater submersible relative to the ocean current. According to the traditional adaptive control law [16], the dynamic control law is designed as follows:

$$\tau = \Phi(\dot{\mathbf{v}}_r, \mathbf{v}_r, \mathbf{v}, \eta) \hat{\theta}_1 - K_d s \quad (8)$$

where  $s = \dot{\mathbf{e}}_c + 2\Lambda \mathbf{e}_c + \Lambda^2 \int \mathbf{e}_c$  is constructed to reduce steady-state error. The adaptive update rate of the parameter  $\hat{\theta}_1$  is  $\dot{\hat{\theta}}_1 = -\Gamma \Phi^T(\dot{\mathbf{v}}_r, \mathbf{v}_r, \mathbf{v}, \eta) s$  (assume  $\dot{\hat{\theta}}_1 = 0$ ).

### III. SIMULATION RESULTS AND ANALYSIS

#### A. The Thruster Arrangement of the Deep-sea Warrior HOV

The Deep-sea Warrior HOV is another breakthrough in the field of deep-sea equipment after 7000m-HOV. Statistically, the localization rate of the Deep-sea Warrior HOV has reached 95%. Fig. 4 shows the thruster configuration of the Deep-sea Warrior HOV. It is equipped with six thrusters, each marked as:  $T^i, i \in [1, 6]$ .

For the Deep-sea Warrior HOV, it is assumed that the parameters of each thruster are the same. It is basically consistent with the real situation and simplified:

$$\tau = [\tau_x \quad \tau_y \quad \tau_z \quad \tau_K \quad \tau_M \quad \tau_N]^T = \mathbf{B} \cdot \mathbf{T} = \mathbf{B} \cdot \begin{bmatrix} T^1 \\ T^2 \\ T^3 \\ T^4 \\ T^5 \\ T^6 \end{bmatrix} \quad (9)$$

where  $\mathbf{B}$  is thruster configuration matrix. According to the thrusters' arrangement of the Deep-sea Warrior HOV, the thruster configuration matrix  $\mathbf{B}$  can be got as follows:

$$\mathbf{B} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & -l_{3y} & l_{3y} & l_{5z} & -l_{6x} \\ -l_{6y} & l_{6y} & -l_{3x} & l_{3x} & 0 & l_{6x} \\ l_{6y} & l_{6y} & 0 & 0 & l_{5x} & 0 \end{bmatrix} \quad (10)$$

where  $l_{3x}, l_{3y}, l_{5x}, l_{5z}, l_{6x}, l_{6y}$  are constant distances between thrusters of the Deep-sea Warrior HOV (shown in Fig. 4).

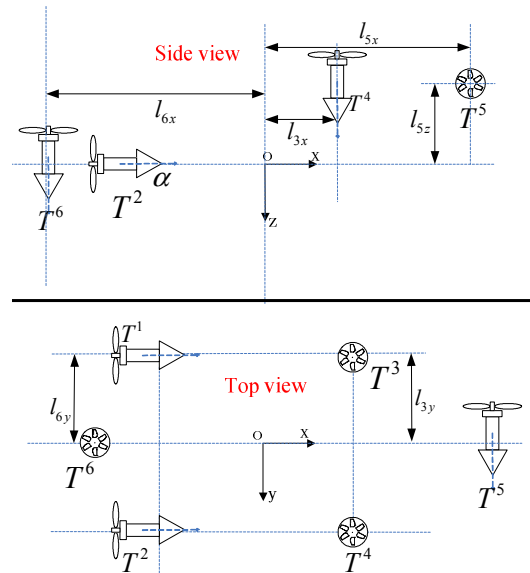


Fig. 4 Thruster configuration

The hydrodynamic parameters of Deep-sea Warrior HOV are listed in Table I, and its dynamic model is shown in (11).

$$\begin{cases} \tau_x = m(\dot{u} - vr) - \frac{1}{2}\rho L^2(X'_{uu}u^2 + X'_{vv}v^2 + X'_{ww}w^2 + X'_{uw}uw) \\ \quad - \frac{1}{2}\rho L^3 X'_{vr}vr - \frac{1}{2}\rho L^4 X'_{rr}r^2 \\ \tau_y = m(\dot{v} + ur) - \frac{1}{2}\rho L^2[Y'_{uv}uv + Y'_{vw}vw + Y'_{v|v}|(v^2 + w^2)^{1/2}] \\ \quad - \frac{1}{2}\rho L^3 Y'_{rr}r^2 \\ \tau_z = m\dot{w} - \frac{1}{2}\rho L^2[Z'_{uw}uw + Z'_{|w|w}|w| + Z'_{ww}|w|(v^2 + w^2)^{1/2}] \\ \quad + Z'_{vv}v^2 + Z'_{|v|w}|v|w + Z'_{w|w}|w|(v^2 + w^2)^{1/2}] - \frac{1}{2}\rho L^3 Z'_{vr}vr \\ \tau_N = I_z \dot{r} - \frac{1}{2}\rho L^3[N'_{uv}uv + N'_{v|v}|v|(v^2 + w^2)^{1/2} + N'_{vw}vw] \\ \quad - \frac{1}{2}\rho L^4[N'_{ur}ur + N'_{|v|r}|v|(v^2 + w^2)^{1/2}|r| - \frac{1}{2}\rho L^5 N'_{r|r}|r|^2] \end{cases} \quad (11)$$

TABLE I  
THE HYDRODYNAMIC PARAMETERS OF DEEP-SEA WARRIOR HOV

$X'_{u} = -21.12$	$X'_{uu} = -31.17$	$X'_{vv} = 3.44$	$X'_{ww} = 27.39$
$X'_{rr} = 9.267$	$X'_{uv} = 8.06$	$X'_{vr} = 13.56$	$Y'_{v} = -132.206$
$Y'_{r} = 1.827$	$Y'_{v} = -251.81$	$Y'_{r} = 1.827$	$Y'_{ v } = -306.12$
$Y'_{ v } = -137.78$	$Y'_{r v } = 1.25$	$Y'_{vw} = 263.41$	$Z'_{w} = -116.125$
$Z'_{w} = -101.67$	$Z'_{ w } = 37.25$	$Z'_{w w } = -337$	$Z'_{vw} = -116.17$
$Z'_{vv} = -38.04$	$Z'_{rr} = -55.75$	$Z'_{vr} = 93.37$	$Z'_{ v w} = 73.93$
$N'_{v} = 1.827$	$N'_{r} = -4.916$	$N'_{v} = -65.04$	$N'_{r} = -39.94$
$N'_{ v } = 31.72$	$N'_{ v r} = -97.93$	$N'_{r v } = -6.699$	$N'_{vw} = -18.606$

### B. 3D Straight Line Tracking

#### 1) The simulation without considering the thrust constraint

The tracking control is carried out for the typical 3D trajectory: 3D straight line. Assuming the actual initial position of HOV is  $(0 \ -5 \ 0 \ \pi/4)$  and the expected initial state is  $(0 \ 0 \ 0 \ \pi/4)$ . The simulation time is set from 0 to 200s. Assume that the HOV trajectory of expectation tracking is:  $x_d = 0.15t$ ,  $y_d = 0.15t$ ,  $z_d = 0.15t$ ,  $\psi_d = \pi/4$ . It is assumed that there is always an ocean current in the inertial coordinate system, and its value is  $\mathbf{v}_E = [u_x \ u_y \ u_z]^T = [0.2 \ 0.2 \ 0.2]^T$ . The controller parameters settings are given below.

The controller parameters of the traditional adaptive method:  $\Gamma=1$ ;  $k_d = 2500$ ;  $\lambda=0.1$ .

The controller parameters of quantum-behaved particle swarm optimization model predictive control (QPSO-MPC) adaptive method:  $N_p = 10$ ;  $N_c = 10$ ;  $\Gamma=1$ ;  $k_d = 2500$ ;  $\lambda=0.1$ .

Fig. 5 shows the tracking trajectories of two methods. Fig. 6 is the corresponding error in the tracking process. Fig. 7 indicates the control thrust of six thrusters (two black dashed lines represent these maximum thrusts, which are 880N and -880N). Fig. 8 lists the absolute value of maximal  $T^1$ ,  $T^2$ ,  $T^3$ ,  $T^4$ ,  $T^5$  and  $T^6$  generated by two methods.

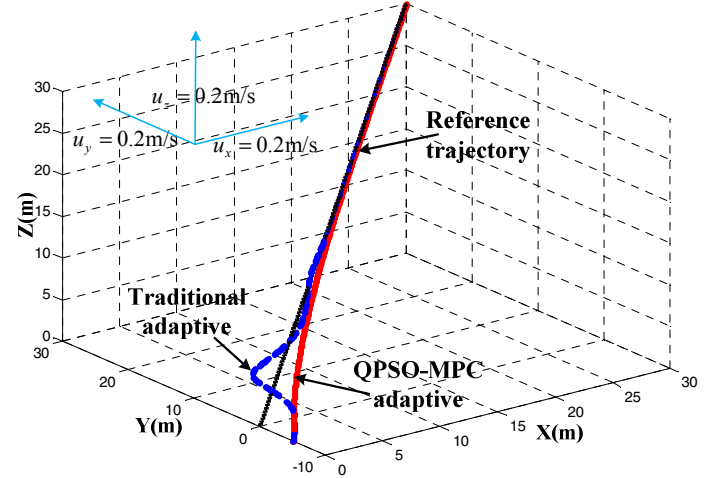


Fig. 5 3D straight line tracking in the current environment

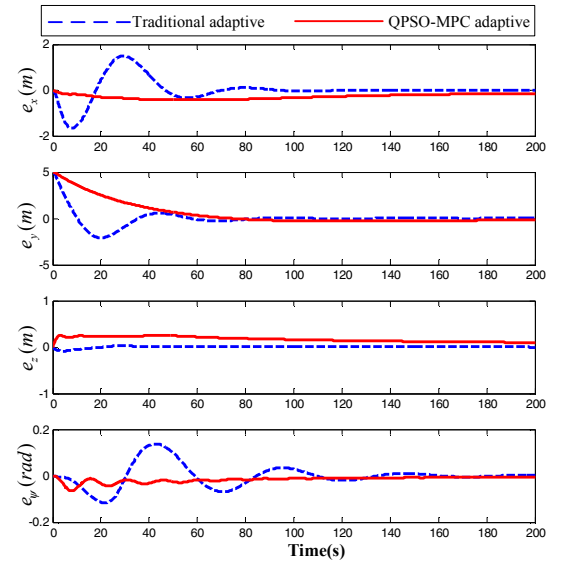


Fig. 6 3D straight line tracking error

Obviously, from Fig. 5 and 6, the tracking result of QPSO-MPC adaptive method is superior to the traditional adaptive method. The chattering problem still exists in the traditional adaptive method due to control law directly related to the initial position error, it can't keep up with the reference trajectory quickly. It takes a long time to control the parameters to adapt to the changes of the ocean current environment. QPSO-MPC adaptive method, due to its speed constraint ability and dual feedback mechanism, does not cause excessive control thrust with the large initial position

error. It can also be observed from Fig. 7 and Fig. 8 that the maximum thrust of six thrusters generated by QPSO-MPC adaptive method is obviously smaller than that of the traditional adaptive method and all within the maximum thrust range. Because of overshoot, the traditional adaptive method has the fluctuation of thrust and  $T^2$ ,  $T^5$  are exceed the range  $[-880N \ 880N]$ . Although QPSO-MPC adaptive method has some fluctuations in the initial stage, the fluctuation amplitude and the time of stabilization are smaller than the traditional adaptive method.

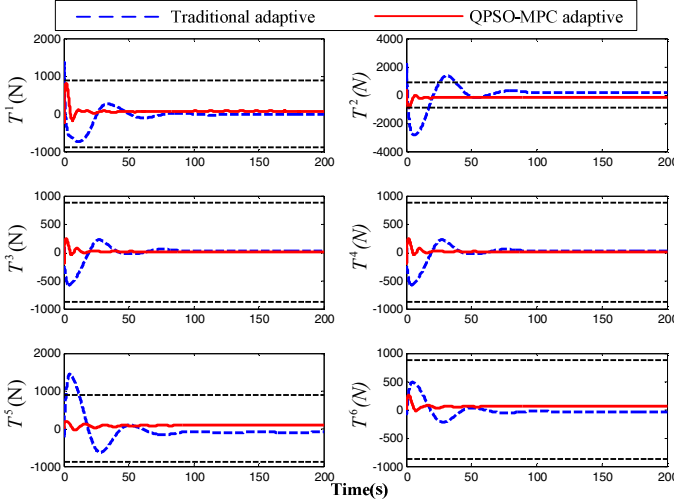


Fig. 7 3D straight line tracking control thrust

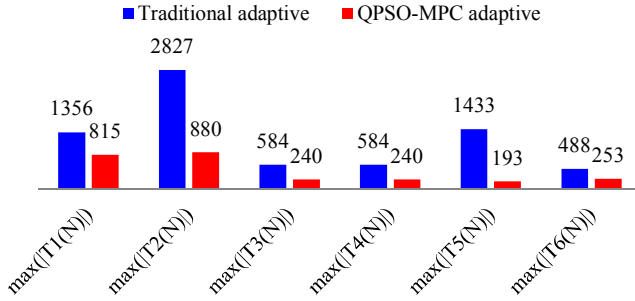


Fig. 8 The absolute value of maximal six thrusts calculated by two control methods

## 2) The simulation with considering the thrust constraint

This section also shows the comparison between two methods in the case of thrust constraints. The simulation parameters are the same as in Section III.B. 1). Fig. 9 shows the tracking effect of two methods with the thrust constraint, and Fig. 10 shows the curve of thrust variation in the tracking process. From Fig. 10, for both the traditional adaptive control method and QPSO-MPC adaptive control method, the thrust has been generated within the maximum thrust range. Therefore, it can be seen that the thrust constraint has been taken effect. Then observing the tracking performance of two methods in Fig. 9, the tracking performance of QPSO-MPC adaptive control is better. The tracking task is basically completed and the thrusts are within a specified range. However, the traditional adaptive control method has the

divergence phenomenon caused by insufficient thrust supply and can't complete the tracking task.

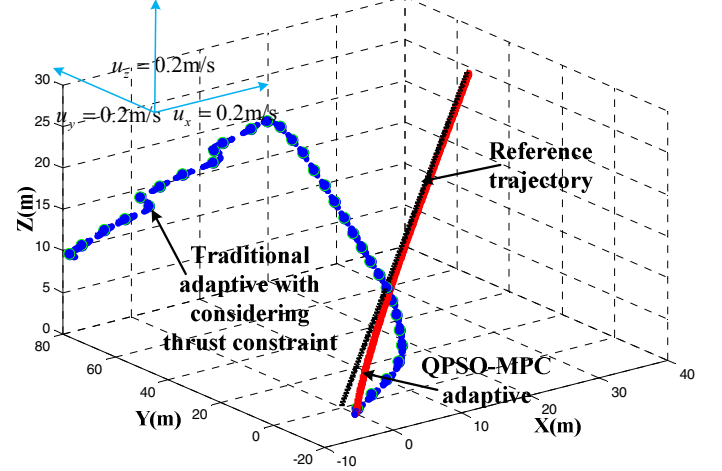


Fig. 9 3D straight line tracking with considering thrust constraint

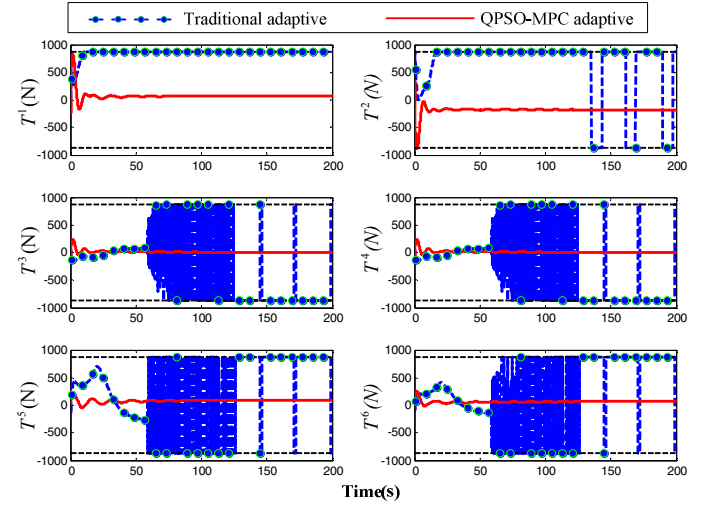


Fig. 10 3D straight line tracking control thrust with considering thrust constraint

## IV. CONCLUSION

In this paper, a model predictive adaptive control strategy is proposed for trajectory tracking control in the ocean current environment. For some hardware constraints of underwater submersible, the model predictive control method is applied to kinematics control to achieve position tracking control satisfying speed constraints. On the other hand, the incremental speed constraints in kinematics further ensure the thrust constraint in dynamic control. Dynamics controller can not only achieve better adaptive control in the ocean current environment, but also satisfy thrust constraint. Compared with the traditional adaptive control method, the effectiveness of the proposed method is verified.

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