Letter

Robust Control of Manned Submersible Vehicle With Nonlinear MPC and Disturbance Observer

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Dear Editor,

This letter focuses on the trajectory tracking of 7000 m JIAOLONG manned submersible vehicle (MSV) with disturbances. The robust controller is realized by a composite control law, where an analytical nonlinear model predictive control (MPC) component is proposed to meet the requirements on tracking performance, and a feedforward control component is developed to reject the external disturbance and model uncertainty on the basis of a disturbance observer (DOB). Furthermore, the stability of the MSV system is analyzed, and representative simulation results are also given. The most significant feature of the designed MPC controller is that an explicit control law can be obtained for the MSV system, which alleviates the computational burden largely.

Introduction: JIAOLONG is the first deep-ocean MSV independently devised and developed by China. The designed maximal depth is 7000 m, which was the deepest submersible all over the world. The MSV can serve in 99.8% of the world's ocean area, which is of great importance for the exploration of deep-ocean resources [1] and [2].

The MSV system works in a complex challenging environment, where the MSV frequently receives external disturbances and parameter perturbations [3]. Owing to the complexity of deep-ocean environment, the nonlinearity of MSV, and the difficulty to acquire precise system parameters and external disturbances, the robust controller design of MSV is a quite challenging issue [4] and [5]. Furthermore, trajectory tracking is an important task for autonomous vehicles. There are some recent research results on the trajectory tracking of unmanned surface vehicle (USV) [6], [7] and MSV [8] with disturbances and uncertainties.

As we know, MPC framework calculates the control law with an on-line optimization problem, which can be used to address the tracking task of autonomous vehicles [9] and [10]. However, the on-line optimization problem in conventional MPC greatly increases the computational burden of the on-board computer, which may lead to the deterioration of real-time capability of control systems. Reference [11] proposes an explicit nonlinear MPC method with analytical solution, which eliminates the calculation of on-line optimization. Hence, it is desirable to develop the controller of MSV with explicit MPC to reduce the computational burden largely.

As previous mentioned, the MSV will encounter multiple disturbances in challenging underwater environments, including external disturbance, model uncertainty, etc. Reference [12] proposes a disturbance observer-based control (DOBC) method, which estimates and then compensates the lumped disturbance of nonlinear systems effectively. The DOBC and related methods have been intensively investigated in recent two decades [13]–[16].

A disturbance observer-based model predictive control (DOB-MPC) scheme is developed for the MSV subject to multiple disturbances. The lumped disturbances are reconstructed by the nonlinear disturbance observer (NDOB), and then rejected with feedforward control technique. An explicit nonlinear MPC control law is proposed for the trajectory tracking of MSV system. Finally, the closed-loop MSV system is proven to be input-to-state stable (ISS), and the simulations verify the superiority of the proposed robust controller.

Problem formulation: We first introduce the mathematical model of JIAOLONG

$$\begin{cases} \dot{\eta} = J(\eta)\nu \\ (M+\Delta M)\dot{\nu} + (C(\nu)+\Delta C(\nu))\nu + (D(\nu)+\Delta D(\nu))\nu \\ \quad +(G(\eta)+\Delta G(\eta)) = f + d \end{cases} \tag{1}$$

where $\eta = [x,y,z,\phi,\theta,\psi]^T$ is the position and orientation in inertial coordinate, and $\nu = [u,v,w,p,q,r]^T$ is the velocity vector in body-fixed coordinate. $J(\eta) \in \mathbb{R}^{6\times 6}$ is the transformation matrix. $M \in \mathbb{R}^{6\times 6}$ and $C(\nu) \in \mathbb{R}^{6\times 6}$ are the intertial matrix and coriolis force matrix, respectively. $D(\nu) \in \mathbb{R}^{6\times 6}$ denotes the viscous resistance, and $G(\eta) \in \mathbb{R}^6$ denotes the vector of gravity and buoyancy. ΔM, $\Delta C(\nu)$, $\Delta D(\nu)$, $\Delta G(\eta)$ denote the parameter perturbations.

The notation $f \in \mathbb{R}^6$ denotes the force vector produced by axial thrusts, and $d \in \mathbb{R}^6$ is the unknown external disturbance. In addition, the detailed thrusters configuration of the MSV can be found in [17]. The MSV is equipped with eight thrusters that are marked by T^i for $i = 1,\ldots,8$. The thruster configuration equation can be described by $f = BT$, where $T = [T^1,\ldots,T^8]^T \in \mathbb{R}^8$ and $B \in \mathbb{R}^{6\times 8}$ represent the thrust vector and configuration matrix, respectively.

Main results: This letter introduces a robust control scheme of MSV based on DOB-MPC method, which can not only suppress the lumped disturbances, but also meet the tracking performance specifications.

The MSV system (1) is rewritten by

$$\begin{cases} \dot{\eta} = J\nu \\ \dot{\nu} = F + G_1 T + G_2 W \end{cases} \tag{2}$$

where $F = M^{-1}(-G - C\nu - D\nu)$, $G_1 = M^{-1}B$, and $G_2 = M^{-1}$. $W = d - \Delta M\dot{\nu} - \Delta C\nu - \Delta D\nu - \Delta G$ denoting the lumped disturbance containing external disturbance and model uncertainty.

The NDOB is designed as

$$\begin{cases} \dot{P} = -LG_2P - L(G_2L\nu + F + G_1T) \\ \hat{W} = P + L\nu \end{cases} \tag{3}$$

where $\hat{W}$ denotes the estimate of lumped disturbance, P denotes an internal state vector, L denotes the observer gain.

Assumption 1: The disturbance $W(t)$ and its derivative $\dot{W}(t)$ are bounded. Moreover, $\bar{W} = \sup_{t\geq 0}(\|W(t)\|)$, $\bar{\dot{W}} = \sup_{t\geq 0}(\|\dot{W}(t)\|)$.

Lemma 1: The estimation error of the NDOB (3) can converge to the neighbourhood of the origin, if $LG_2 > 0$ holds.

Proof: The derivative of $\hat{W}$ along time is given by

$$\dot{\hat{W}} = \dot{P} + L\dot{\nu} = -LG_2P - LG_2L\nu + LG_2W. \tag{4}$$

Substituting $P = \hat{W} - L\nu$ into (4), we have

$$\dot{\hat{W}} = LG_2(W - \hat{W}). \tag{5}$$

Letting $e = W - \hat{W}$, we can obtain

$$\dot{e} + LG_2e = \dot{W}. \tag{6}$$

Considering the Assumption 1, we have

$$\dot{e} + LG_2e \leq \bar{\dot{W}}. \tag{7}$$

Solving the differential inequality (7), we obtain

$$e(t) \leq \frac{\bar{\dot{W}}}{LG_2} + \left[e(0) - \frac{\bar{\dot{W}}}{LG_2}\right]\exp(-LG_2t). \tag{8}$$

It can be seen that $e(t) \to \frac{\bar{\dot{W}}}{LG_2}$ as $t \to \infty$, if $LG_2 > 0$ holds. Further-

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more, by selecting a large matrix LG_2, we can drive the estimation error $e(t)$ into a small region of the origin. ■

In what follows, we will design the control vector T of MSV by using the explicit nonlinear MPC.

The selected optimization objective function is given by

$$O=\frac{1}{2}\int_0^{T_p}(\hat{\eta}(t+\tau)-\eta_r(t+\tau))^T Q(\hat{\eta}(t+\tau)-\eta_r(t+\tau))d\tau \tag{9}$$

where $\eta_r(t+\tau)$ denotes the reference trajectory, $\hat{\eta}(t+\tau)$ denotes the predicted trajectory, T_p denotes the predictive horizon, and Q is the weighting matrix.

Using Taylor series expansion with some higher-order terms, the predicted value of $\hat{\eta}(t+\tau)$ at time instant t can be obtained as

$$\hat{\eta}(t+\tau)\approx\eta(t)+\tau\dot{\eta}(t)+\cdots+\frac{\tau^{r_c+r_d}}{(r_c+r_d)!}\eta^{[r_c+r_d]}(t) \tag{10}$$

where r_c is the control order, and r_d is the input relative degree. According to [11], if r_d is less than 4, r_c can be chosen arbitrarily. However, in order to save control energy, r_c shall be chosen as small as possible.

The derivatives of the output of system (2) are derived by

$$\dot{\eta}=J\nu \tag{11}$$

$$\ddot{\eta}=\dot{J}\nu+J(F+G_1T+G_2W). \tag{12}$$

We can observe that the control input T appears in the second-order derivative of the output η, which implies that the input relative degree of MSV is $r_d=2$. Therefore, whatever control order is selected, the system can be stabilized. Therefore, to save control effort, the control order is selected as $r_c=0$.

Theorem 1: If the explicit MPC control law is designed by

$$T=G_1^{\dagger}\left(J^{-1}(-K(\bar{\Theta}-\bar{\Theta}_r)+\tilde{\Theta}_r-\dot{J}\nu)-F-G_2\hat{W}\right) \tag{13}$$

where $K=[k_0I_{6\times6},k_1I_{6\times6}]$, $\bar{\Theta}=[\eta^T,\dot{\eta}^T]^T$, $\bar{\Theta}_r=[\eta_r^T,\dot{\eta}_r^T]^T$, $\tilde{\Theta}_r=\ddot{\eta}_r$, and $G_1^{\dagger}$ denotes the pseudo-inverse of matrix G_1, then the tracking error of MSV will converge into a small region of the origin.

Proof: With the Taylor series expansion, we have

$$\hat{\eta}(t+\tau)=\begin{bmatrix}\bar{\Gamma} & \tilde{\Gamma}\end{bmatrix}\begin{bmatrix}\bar{\Theta}\\ \tilde{\Theta}\end{bmatrix} \tag{14}$$

where $\bar{\Gamma}=[I_{6\times6},\tau I_{6\times6}]$, $\tilde{\Gamma}=\frac{\tau^2}{2!}I_{6\times6}$, and $\tilde{\Theta}=\ddot{\eta}$.

The future value of the reference trajectory can be described as

$$\eta_r(t+\tau)=\begin{bmatrix}\bar{\Gamma} & \tilde{\Gamma}\end{bmatrix}\begin{bmatrix}\bar{\Theta}_r\\ \tilde{\Theta}_r\end{bmatrix}. \tag{15}$$

Substituting (14) and (15) into objective function (9), it leads to

$$\begin{aligned}O&=\frac{1}{2}\int_0^{T_p}\begin{bmatrix}\bar{\Theta}-\bar{\Theta}_r\\ \tilde{\Theta}-\tilde{\Theta}_r\end{bmatrix}^T\begin{bmatrix}\bar{\Gamma}^T\sqrt{Q}\\ \tilde{\Gamma}^T\sqrt{Q}\end{bmatrix}\begin{bmatrix}\sqrt{Q}\bar{\Gamma}^T\\ \sqrt{Q}\tilde{\Gamma}^T\end{bmatrix}^T\begin{bmatrix}\bar{\Theta}-\bar{\Theta}_r\\ \tilde{\Theta}-\tilde{\Theta}_r\end{bmatrix}d\tau\\ &=\begin{bmatrix}\bar{\Theta}-\bar{\Theta}_r\\ \tilde{\Theta}-\tilde{\Theta}_r\end{bmatrix}^T\begin{bmatrix}\Gamma_1 & \Gamma_2\\ \Gamma_2^T & \Gamma_3\end{bmatrix}\begin{bmatrix}\bar{\Theta}-\bar{\Theta}_r\\ \tilde{\Theta}-\tilde{\Theta}_r\end{bmatrix}\end{aligned} \tag{16}$$

where $\Gamma_1=\int_0^{T_p}\bar{\Gamma}^TQ\bar{\Gamma}d\tau$, $\Gamma_2=\int_0^{T_p}\bar{\Gamma}^TQ\tilde{\Gamma}d\tau$, and $\Gamma_3=\int_0^{T_p}\tilde{\Gamma}^TQ\tilde{\Gamma}d\tau$.

According to the partial derivative of objective function O with respect to control input T, the necessary condition for the optimal control T is given by

$$\frac{\partial O}{\partial T}=2\left(\frac{\partial(\tilde{\Theta}-\tilde{\Theta}_r)}{\partial T}\right)^T[\Gamma_2^T(\bar{\Theta}-\bar{\Theta}_r)+\Gamma_3(\tilde{\Theta}-\tilde{\Theta}_r)]=0. \tag{17}$$

It is easy to observe that $\frac{\partial(\tilde{\Theta}-\tilde{\Theta}_r)}{\partial T}$ is nonsingular. Hence, if the second term equals to zero, (17) holds, which gives rise to

$$\tilde{\Theta}=-\Gamma_3^{-1}\Gamma_2^T(\bar{\Theta}-\bar{\Theta}_r)+\tilde{\Theta}_r. \tag{18}$$

Let $K=\Gamma_3^{-1}\Gamma_2^T$. Considering (12) and (18), we can obtain

$$\dot{J}\nu+J(F+G_1T+G_2W)=-K(\bar{\Theta}-\bar{\Theta}_r)+\tilde{\Theta}_r. \tag{19}$$

Replacing W with its estimation $\hat{W}$ in (19), we can obtain the nonlinear control law (13) in the Theorem 1.

Substituting (13) into (12), and letting $e_\eta=\eta-\eta_r$, we have

$$\begin{aligned}\ddot{\eta}&=\dot{J}\nu+J(F+G_1G_1^{\dagger}(J^{-1}(-K(\bar{\Theta}-\bar{\Theta}_r)+\tilde{\Theta}_r-\dot{J}\nu)\\ &\quad-F-G_2\hat{W})+G_2W)\\ &=-K(\bar{\Theta}-\bar{\Theta}_r)+\tilde{\Theta}_r+JG_2(W-\hat{W})\\ &=-\begin{bmatrix}k_0I_{6\times6} & k_1I_{6\times6}\end{bmatrix}\begin{bmatrix}(\eta-\eta_r)\\ (\dot{\eta}-\dot{\eta}_r)\end{bmatrix}+\ddot{\eta}_r+JG_2(W-\hat{W}).\end{aligned} \tag{20}$$

Hence, we can acquire the following closed-loop dynamics:

$$\ddot{e}_\eta+k_1\dot{e}_\eta+k_0e_\eta=JG_2e \tag{21}$$

where e is the disturbance estimation error. k_0 and k_1 depend on the horizon T_p and control order r_c, which can be selected to make the polynomial $s^2+k_1s+k_0$ Hurwitz.

Defining $\sigma=\begin{bmatrix}e_\eta & \dot{e}_\eta\end{bmatrix}$ and $\omega=JG_2e$, we derive that

$$\dot{\sigma}=A_\sigma\sigma+B_\omega\omega \tag{22}$$

where $A_\sigma=\begin{bmatrix}0_{6\times6} & I_{6\times6}\\ -k_1I_{6\times6} & -k_0I_{6\times6}\end{bmatrix}$ and $B_\omega=\begin{bmatrix}0_{6\times6}\\ I_{6\times6}\end{bmatrix}$. We choose a Lyapunov function candidate as $V(\sigma)=\sigma^TP_\sigma\sigma$, where P_σ satisfies $A_\sigma^TP_\sigma+P_\sigma A_\sigma=-Q_\sigma$ with $Q_\sigma>0$. Then, we obtain

$$\begin{aligned}\dot{V}(\sigma)&=\sigma^T(A_\sigma^TP_\sigma+P_\sigma A_\sigma)\sigma+2\sigma^TP_\sigma B_\omega\omega\\ &\le-\sigma^TQ_\sigma\sigma+2\|\sigma\|\lambda_{\max}(P_\sigma)\|\omega\|\\ &\le-(1-\alpha)\sigma^TQ_\sigma\sigma-\alpha\sigma^TQ_\sigma\sigma+2\|\sigma\|\lambda_{\max}(P_\sigma)\|\omega\|\end{aligned} \tag{23}$$

with $0<\alpha<1$. We have

$$\dot{V}(\sigma)\le-(1-\alpha)\sigma^TQ_\sigma\sigma,\quad\forall\|\sigma\|\ge\frac{2\lambda_{\max}(P_\sigma)\|\omega\|}{\alpha\lambda_{\min}(Q_\sigma)}. \tag{24}$$

Define $\mu=\frac{2\lambda_{\max}(P_\sigma)\|\omega\|}{\alpha\lambda_{\min}(Q_\sigma)}$, and the Lyapunov function V satisfies the inequality: $\lambda_{\min}(P_\sigma)\|\sigma\|^2\le V(\sigma)\le\lambda_{\max}(P_\sigma)\|\sigma\|^2$. According to Theorem 4.18 of [18], we can derive the ultimate bound as

$$\bar{\sigma}=\sqrt{\frac{\lambda_{\max}(P_\sigma)}{\lambda_{\min}(P_\sigma)}}\mu=\sqrt{\frac{\lambda_{\max}(P_\sigma)}{\lambda_{\min}(P_\sigma)}}\frac{2\lambda_{\max}(P_\sigma)}{\alpha\lambda_{\min}(Q_\sigma)}\|\omega\| \tag{25}$$

which means $\|e_\eta(t)\|\le\|\sigma(t)\|\le\bar{\sigma}$. Considering Lemma 1 and the relationship $\omega=JG_2e$, we have that $\|\omega\|$ also is a relatively small value. Therefore, the tracking error $e_\eta(t)$ will converge into a small region of the origin. ■

Simulation tests: In this section, the superior control performance of the designed DOB-MPC scheme are verified by simulations.

The detailed parameters of the MSV system can be found in literature [17]. The control parameters are given by $L=70I_{6\times6}$, $T_p=2$ s, $r_c=0$, and $Q=2I_{6\times6}$. The sampling period is $\tau=50$ ms. The lumped disturbance and reference trajectory are given as follows. The external disturbance $d_j=\sum_{i=1}^N A_{i1}\cos(\omega_it+\alpha_i)+A_{i2}\sin(\omega_it+\alpha_i)$ is injected into the MSV system [19]. Additionally, 10% uncertainty of the model parameters is also considered in the simulations. The spiral trajectory to be tracked is described by $x_d=10\sin(0.04\pi t)$, $y_d=-10\cos(0.04\pi t)+10$, $z_d=0.2t$, $\phi_d=0.1\sin(0.02t)$, $\theta_d=-0.05\times\sin(0.02t)$, $\psi_d=0.005\pi t$. Furthermore, to demonstrate the superior performance of the designed DOB-MPC scheme clearly, the integral model predictive control (I-MPC) method and disturbance observer based sliding mode control (DOB-SMC) method are used as comparisons. The control law of I-MPC is designed by $T_{\rm int}=T_{\rm mpc}+B^{\dagger}K_I\int_0^t[\eta(s)-\eta_r(s)]ds$, where $T_{\rm mpc}$ is the nominal explicit MPC control law, $K_I=50$ is the integral coefficient. The control law of DOB-SMC is described by $T_{\rm smc}=G_1^{\dagger}J^{-1}[-c_sJ\nu-JG_2\hat{W}-JF-\dot{J}\nu-K_s{\rm sign}(\varepsilon)]$, where $\varepsilon=(\dot{\eta}-\dot{\eta}_d)+c_s(\eta-\eta_d)$ is the sliding surface, $c_s=5$, $K_s=0.5$.

The disturbance estimation of NDOB is depicted in Fig. 1. It can be seen that the NDOB can estimate the disturbance quickly and accurately. Fig. 2 shows the three-dimensional tracking result of spiral trajectory. The proposed DOB-MPC scheme can drive the MSV to track the spiral trajectory more accurately than the I-MPC method and the DOB-SMC method. Additionally, the root-mean-square (RMS) values of tracking error are listed in Table 1, which verifies that DOB-MPC can achieve the smallest tracking errors. Further-

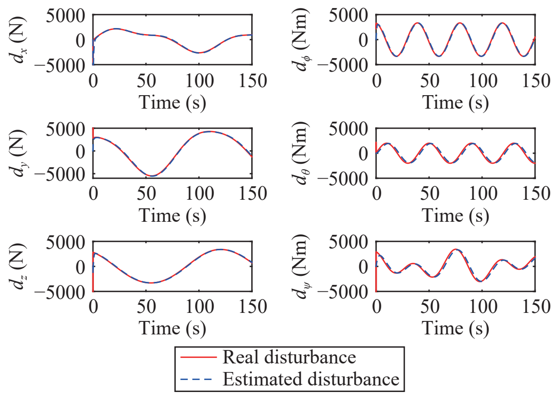

Fig. 1. The estimated disturbances.

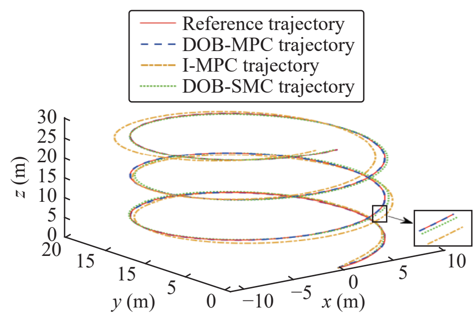

Fig. 2. The trajectory tracking spiral with three dimensions.

Table 1. The RMS of Tracking Error

Control methods	DOB-MPC	I-MPC	DOB-SMC
$(e_x)_{RMS}$ (m)	0.0097	0.7396	0.2736
$(e_y)_{RMS}$ (m)	0.0126	0.3916	0.2359
$(e_z)_{RMS}$ (m)	0.0214	0.5654	0.1114
$(e_\phi)_{RMS}$ (rad)	0.0154	0.1981	0.0347
$(e_\theta)_{RMS}$ (rad)	0.0301	0.1209	0.0421
$(e_\psi)_{RMS}$ (rad)	0.0303	0.1350	0.0736

more, the control input signals are illustrated in Fig. 3. All the control input signals of DOB-MPC method are smooth. However, the control input signals of DOB-SMC method have large chattering that is not allowed in practical engineering systems. Because the severe chattering phenomenon will shorten the life of thrusters, and even cause the damage of thrusters.

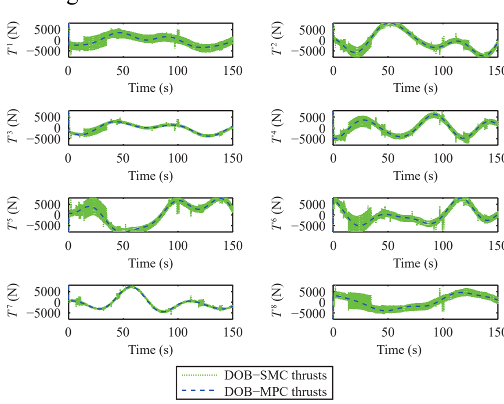

Fig. 3. The thrusts of MSV system.

In summary, the superiority of the designed DOB-MPC scheme is verified by simulations, which is able to reject the lumped disturbance and achieve satisfactory tracking performance for MSV.

Conclusions: In this letter, a robust controller is developed with DOB-MPC method for the MSV system subject to model uncertainty and external disturbance. The lumped disturbance is estimated by NDOB, and the estimation information is then integrated into the design of the explicit nonlinear MPC control law. The proposed DOB-MPC scheme can obtain satisfactory tracking performance and disturbance-rejection capability for the MSV system.

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