NMPC-Based Obstacle Avoidance for Omni-Directional Intelligent Navigator Using APF

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Abstract. This paper presents the Nonlinear Model Predictive Control (NMPC) strategy for controlling Omni Directional Intelligent Navigator (ODIN) embedded with Artificial Potential Field algorithm (APF) for obstacle avoidance. NMPC is a optimal control method in controlling a system with high nonlinearity such as ODIN. Moreover, APF is a simple but effective tool for ODIN to operate in such an obstacle-dense marine environment. The simulation in MATLAB illustrates effective trajectory tracking and obstacle-avoidance of the proposed controller.

Keywords: Omni Directional Intelligent Navigator, Nonlinear Model Predictive Control, Artificial Potential Field.

1 Introduction

Nowadays, underwater robots have become increasingly focused on by researchers for ocean exploration and exploitation. Controlling AUVs is a difficult task due to various factors such as the nonlinearity of robot dynamics, unknown disturbances and obstacle avoidance.

ODIN (Omni Directional Intelligent Navigator) was developed in January 1996 by the University of Hawaii. The robot is an omni-directional underwater vehicle with 8 actuators for travelling and capable of autonomous operations. Because of complex spatial constraints of the marine environment, robust motion planning and obstacle avoidance strategies are required for ODIN.

Traditional control methods were initially developed for ODIN such as PD and PID[1][2][3].Adaptive-learning control method was also used in ODIN [4].Dead zone and thrusters saturation was considered for ODIN fine motion control in [5].A fault-tolerant controller was devised in [6] for fault detection, fault isolation and fault accommodation in ODIN robot. However, due to the strong nonlinear dynamics of ODIN, these control strategies have limitations in accuracy. To deal with such problems, State-Dependent Riccati Equation (SDRE)–based optimal control was implemented in [7]. Researchers also devised a nonsingular fast terminal sliding-mode controller method for the ODIN dynamic [8]. This paper proposes the Nonlinear Model Predictive Control method. The capability of Nonlinear Model Predictive Control (NMPC) in calculating future system states and minimizing a predefined cost function over a prediction horizon allows it to determine optimal control input. This predictive estimation enables NMPC to enhance stability and control performance. The cost function can also be integrated with control and states constraints.

Artificial Potential Field (APF), proposed by Khatib[9], is a popular reactive navigation method in robotic path planning, used for its simplicity and computational efficiency. APF algorithm using attractive artificial forces to pull the robot toward the goal and repulsive forces to avoid identified obstacles. APF has been used in various underwater vehicles[10–12].

2 ODIN dynamics

The Omni-Directional Intelligent Navigator (ODIN) is a spherical autonomous vehicle (AUV). It contains eight actuators, four of which are vertical thrusters and the other four are horizontal thrusters. This over-actuated robot can travel in 3 dimensions and can perform angular movements (6 DOF).

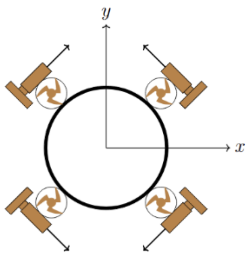

Fig. 1. ODIN geometry

Inertial and Body-fixed reference frames can express the coordination of a marine craft. $\eta = [x, y, z, \phi, \theta, \psi]^T$ is the position and orientation of the ODIN in inertial frame and $\nu = [u, v, w, p, q, r]^T$ is the velocity in the body-fixed frame.

The velocity of the ODIN in inertial frame $\dot{\eta}$ can be transitioned to a body-fixed frame ν with the following equation:

$$\dot{\eta} = J(\eta)\nu \tag{1}$$

where J is the transformation matrix, which is given as:

$$J(\eta) = \begin{bmatrix} R_1(\eta) & \mathbf{0}_{3x3} \\ \mathbf{0}_{3x3} & R_2(\eta) \end{bmatrix} \tag{2}$$

where R_1 and R_2 are the linear and angular velocity, respectively:

$$R_1 = \begin{bmatrix} c(\psi)c(\theta) & c(\psi)s(\theta)s(\phi) - s(\psi)c(\phi) & c(\psi)s(\theta)c(\phi) + s(\psi)s(\phi) \\ s(\psi)c(\theta) & s(\psi)s(\theta)s(\phi) + c(\psi)c(\phi) & s(\psi)s(\theta)c(\phi) - c(\psi)s(\phi) \\ -s(\theta) & c(\theta)s(\phi) & c(\theta)c(\phi) \end{bmatrix} \quad (3)$$

$$R_2 = \begin{bmatrix} 1 & s(\phi)\tan(\theta) & c(\phi)\tan(\theta) \\ 0 & c(\phi) & -s(\phi) \\ 0 & s(\phi)/c(\theta) & c(\phi)/c(\theta) \end{bmatrix} \quad (4)$$

The AUV dynamics can be represented as nonlinear equations of motion in body-fixed frame with no current velocity:

$$\dot{M}\nu + C(\nu)\nu + D(\nu)\nu + G(\eta) + g_o = \tau_v \quad (5)$$

Where:

$$M = M_{rb} + M_A \qquad C(\nu) = C_{rb}(\nu) + C_A(\nu) \quad (6)$$

M_{rb} and C_{rb} are the mass matrix and the Coriolis matrix of the rigid body of ODIN. Because the ODIN is symmetric in all x, y, z axes, the mass and the Coriolis matrices are expressed as:

$$M_{RB} = \begin{bmatrix} mI_{3\times3} & -mS(r_g^b) \\ mS(r_g^b) & I_b \end{bmatrix} \qquad C_{RB} = \begin{bmatrix} mS(\nu_2) - mS(\nu_2)S(r_g^b) \\ mS(\nu_2)S(r_g^b) - S(I_b\nu_2) \end{bmatrix} \quad (7)$$

Where $S(X)$ is the transformation function to the skew matrix. ν_2 is the velocity vector. m is the total mass of the model. r_g^b is the offset vector between the center of gravity and the center of body. If no additional mass is added to the dynamic, r_g^b can be considered as $[0,0,0]^T$. M_A and C_A are the added mass matrix and the Coriolis matrix created by the inertia of the surrounding fluid. $D(\nu)$ is the hydrodynamic damping matrix which contains linear and quadratic drag:

$$D(\nu) = D_{linear} + D_{quadratic} \, |\nu| \quad (8)$$

$G(\eta)$ is the matrix of restoring forces that expresses the gravitational and buoyant forces and moments that act on the ODIN. Due to the symmetric nature of the robot, gravitational forces $W \approx B$ and $G(\eta)$ can be shown as:

$$G(\eta) = \begin{bmatrix} 0 & 0 & 0 & (z_{GW} - z_B)\sin\theta & -(z_{GW} - z_B)\cos\theta\sin\phi & 0 \end{bmatrix}^T \quad (9)$$

where z_G and z_B are the centers of gravity (COF) and center of buoyancy (COB) Equations of motion of the ODIN can also be expressed in NED:

$$M^*(\eta)\ddot{\eta} + C^*(\dot{\eta},\eta)\dot{\eta} + D^*(\dot{\eta},\eta)\dot{\eta} + G^*(\eta) + g_o^* = \tau^* \tag{10}$$

Where:

$$M^*(\eta) = J^{-T}(\eta)MJ^{-1}(\eta); \qquad C^*(\dot{\eta},\eta) = J^{-T}(\eta)\left[C(\nu) - MJ^{-1}(\eta)\dot{J}(\eta)\right]J^{-1}(\eta)$$

$$D(\dot{\eta},\eta) = J^{-T}(\eta)D(\nu)J^{-1}(\eta); \qquad G^*(\eta) + g_o^* = J^{-T}(G(\eta) + g_o); \qquad \tau^* = J^{-T}\tau$$

Thrust force distribution:

$$\tau_\nu = E * u \tag{11}$$

where $u \in \mathbb{R}^8$ is the vector of thrust forces from each actuator. E is the following allocation matrix:

$$\begin{bmatrix} s & -s & -s & s & 0 & 0 & 0 & 0 \\ s & s & -s & -s & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & -1 & -1 & -1 \\ 0 & 0 & 0 & 0 & R_{\text{ver}}s & R_{\text{ver}}s & -R_{\text{ver}}s & -R_{\text{ver}}s \\ 0 & 0 & 0 & 0 & R_{\text{ver}}s & -R_{\text{ver}}s & -R_{\text{ver}}s & R_{\text{ver}}s \\ R_{\text{hor}} & -R_{\text{hor}} & R_{\text{hor}} & -R_{\text{hor}} & 0 & 0 & 0 & 0 \end{bmatrix} \tag{12}$$

Where $s = \dfrac{1}{\sqrt{2}}$, R_{ver} and R_{hor} are the length between the center of the ODIN and the center of each vertical and horizontal thruster, respectively.

3 NMPC-APF for obstacle avoidance

3.1 Non-linear Model Predictive Control

The model predictive control is based on solving the optimal control problem based on the dynamics of the system and constraints of the states and inputs from the controller. The MPC estimates the future behavior of the system over a prediction horizon (T_p). The prediction model is based on this equation:

$$\eta_{k+1} = f(\eta_k, \tau_k) \tag{13}$$

Minimizing a cost function J is set as the control objective on a finite control horizon (T_c):

$$J=\sum_{k=0}^{N-1}\ell(x_k,u_k)+V(x_N) \tag{14}$$

Where l is the stage cost, and V is the terminal cost to ensure stability. Because of the disturbances that can affect the model's motion and feedback, calculating and updating the control signal are necessary for all steps.

State constraints can be applied to the NMPC to ensure distances between the robot and the obstacles.

$$\| x_k - x_{\text{obs}} \| \geq d_{\text{safe}} \tag{15}$$

The control signal τ^* is calculated using optimization problem at step k:

$$\tau^* = \arg\min_u J$$

$$s.t \quad \eta_{k+i+1} = f(\eta_{k+i},\tau_{k+i}), \forall i=\overline{0,T_p}$$

$$\| x_{k+i} - x_{\text{obs}} \| \geq d_{\text{safe}}$$

Where:

$$J(\eta,\eta_r,\tau)=\sum_{i=0}^{T_p+1} e[k+i]^T Q e[k+i] + \sum_{i=0}^{T_c} R\tau[k+i]^2 \tag{17}$$

where:

$\eta = \begin{bmatrix}\eta[k]^T & \eta[k+1]^T & \cdots & \eta[k+T_p+1]^T\end{bmatrix}^T$ is the column matrix of predicted states over the prediction horizon. $\tau = \begin{bmatrix}\tau[k] & \tau[k+1] & \cdots & \tau[k+T_c]\end{bmatrix}^T$ is the column matrix of predicted control signals. $\eta_r = \begin{bmatrix}\eta_r[k] & \eta_r[k+1] & \cdots & \eta_r[k+T_p+1]\end{bmatrix}^T$ is the column matrix of reference signals over the prediction horizon, with $\eta_r[k] = \begin{bmatrix}y_r[k] & \phi_r[k]\end{bmatrix}^T$. $e[k] = \begin{bmatrix}\eta - \eta_r\end{bmatrix}^T$ is the error vector. $Q = Q^T > 0$ and R are weighing matrices for the cost function.

Minimizing the cost function $(J(\eta,\eta_r,\tau)$ yields the optimal control sequence:

$$\tau^* = \begin{bmatrix}\tau^*[k] & \tau^*[k+1] & \cdots & \tau^*[T_c]\end{bmatrix}^T \tag{18}$$

The resulting optimal control sequence τ^* provides the control inputs for the next T_c steps, guiding the system towards the desired behavior while minimizing the cost.

3.2 Artificial potential field

Artificial Potential Field is widely used in obstacle avoidance for path planning for mobile robots. The method contains a combination of attracted force towards set-points and repulsive force to avoid obstacles. The APF framework contains two fundamental functions: Attractive Potential U_{att} and Repulsive Potential U_{rep} .

Attractive Potential draws the robot toward the goal position η_{goal} . A variety of functions can be used as an attractive potential.

Remark 1: In this study, Attractive Potential is unnecessary as the NMPC provides reference tracking.

Repulsive Potential appears near the obstacles and becomes exponentially stronger as the mobile robot approaches. Repulsive Potential is given as:

$$U_{rep,i}(x) = \begin{cases} \frac{1}{2} k_{rep} \left(\frac{d}{\rho(\eta)} - 1 \right)^2 & \text{if } \rho(\eta) \le d, \\ 0 & \text{otherwise.} \end{cases} \tag{19}$$

$\rho(\eta)$ can be defined as:

$$\rho(\eta) = \frac{1}{2}\left(\left(x - x_{obs_i}\right)^2 + \left(y - y_{obs_i}\right)^2 + \left(z - z_{obs_i}\right)^2\right) \tag{20}$$

where x_{obs} , y_{obs} , z_{obs} are the coordination of the i^{th} obstacles visible to the ODIN sensors. Gradient of the repulsive potential field is taken to calculate the force exerted from the repulsive potential:

$$dV_x = k_{rep} \frac{\rho(\eta) - d}{\rho(\eta)^3} \frac{\partial \rho(\eta)}{\partial x}; dV_y = k_{rep} \frac{\rho(\eta) - d}{\rho(\eta)^3} \frac{\partial \rho(\eta)}{\partial y}; dV_z = k_{rep} \frac{\rho(\eta) - d}{\rho(\eta)^3} \frac{\partial \rho(\eta)}{\partial z} \tag{21}$$

This can be directly implemented to the control input τ^* for obstacle avoidance:

$$\tau^* = \tau_{nominal} - [dV_x, dV_y, dV_z, 0, 0, 0]^T \tag{22}$$

4 Simulations

4.1 Simulation setup

The ODIN starts from a stationary position with an initial velocity of zero. A series of waypoints is set and a cscvn function integrated in MATLAB is used to interpolate the trajectory between these waypoints. The sample time is set at T = 0.1 s, the prediction horizon and control horizon are set at Np = 15 and Nc = 10, respectively. For the NMPC weights, the positional variables are set at 5 while the angular variables are 1. Table 1 gives the numerical parameter of the ODIN.

Table 1. ODIN parameters

Description	Variable	Value
Mass of the ODIN	m	34.35 kg
Radius of the ODIN	R	0.2 m
Radius of the vertical thrusters	r_{ver}	0.052 m
Radius of the horizontal thrusters	r_{hor}	0.052 m
Distance between the center of ODIN to the center of vertical thrusters	R_{ver}	0.252 m
Distance between the center of ODIN to the center of horizontal thrusters	R_{hor}	0.356 m

The simulations focus on two primary objectives: trajectory tracking and obstacle avoidance. These objectives are used to evaluate the effectiveness of the propose NMPC-APF strategy.

4.2 Simulation results

The proposed NMPC-APF controller shows great results in terms of trajectory tracking and obstacle-avoidance. The GitHub repository contains codes and simulations results(https://github.com/minhdt0807/NMPC-APF-for-ODIN.git).

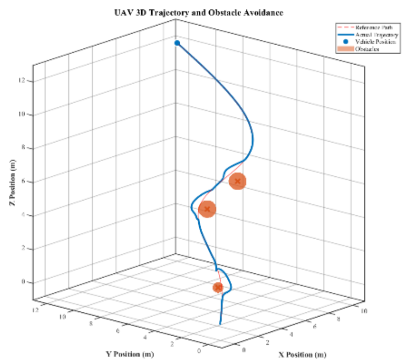

Fig. 2. ODIN 3D trajectory and Obstacle Avoidance Visualization

5 Conclusion

In this paper, the ODIN is manipulated through the proposed controller in simulated 3D marine environment. The NMPC-APF framework combines predictive control strategy with reactive obstacle avoidance algorithm, tackling the adversities of ODIN highly nonlinear dynamics and underwater surroundings. Simulation results validate the effectiveness of the proposed controller in trajectory tracking and obstacle avoidance. Future work may focus on further enhancement of the APF obstacle avoidance algorithm in a more obstacle-dense marine environment.

References

1. Choi HT, Hanai A, Choi SK, Yuh J (2003) Development of an Underwater Robot, ODIN-I11
2. Choi SK, Yuh J, Takashige GY Development of the Omni-Directional Intelligent Navigator
3. Hanai A, Choi HT, Choi SK, Yuh J (2004) Experimental study on fine motion control of underwater robots. In: Advanced Robotics. pp 963–978
4. Choi SK, Yuh J (1996) Experimental Study on a Learning Control System with Bound Estimation for Underwater Robots
5. Hanai A, Choi H, Choi S (2003) Minimum Energy Based Fine Motion Control of Underwater Robots in the Presence of Thruster Nonlinearity
6. Yang KCH, Yuh J, Choi SK (1999) Fault-tolerant system design of an autonomous underwater vehicle ODIN: An experimental study. Int J Syst Sci 30:1011–1019. https://doi.org/10.1080/002077299291877
7. Yim S-B, Oh J-H (2003) A novel approach for the optimal control of autonomous underwater vehicles
8. Ali N, Tawiah I, Zhang W (2020) Finite-time extended state observer based nonsingular fast terminal sliding mode control of autonomous underwater vehicles. Ocean Engineering 218:. https://doi.org/10.1016/j.oceaneng.2020.108179
9. Khatib O Real-Time Obstacle Avoidance for Manipulators and Mobile Robots
10. Zhang Y, Wang Q, Shen Y, et al (2024) Multi-AUV cooperative control and autonomous obstacle avoidance study. Ocean Engineering 304:. https://doi.org/10.1016/j.oceaneng.2024.117634
11. Qian Y, Sun H, Feng S (2023) Obstacle avoidance method of autonomous vehicle based on fusion improved A*APF algorithm. Bulletin of the Polish Academy of Sciences: Technical Sciences 71:. https://doi.org/10.24425/bpasts.2023.144624
12. Song J, Hao C, Su J (2020) Path planning for unmanned surface vehicle based on predictive artificial potential field. Int J Adv Robot Syst 17:. https://doi.org/10.1177/1729881420918461