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Depth Control of the MARES AUV using NMPC

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Abstract

Autonomous Underwater Vehicles (AUV) is a nonlinear system. Difficulties of control system design problems in underwater vehicles due to their nonlinear dynamics, indeterminate models, and the emergence of disturbances that are difficult to measure or estimate. The dynamics of control of the vehicle requires a guarantee of stability and consistent performance. The difficulty of control system design problem in AUV dynamics is the linear traditional design methodology can not be accommodated easily. In this thesis, a nonlinear disturbance observer build derived from predictive control law model, used to predict over prediction horizon to produce control signal sequences in order to follow the reference that given, noise cancelation, and online optimization, so NMPC applied directly to nonlinear model without doing linearization in advance to solve the problem of tracking control in depth control on the MARES AUV. The simulation results show that NMPC controllers herd the depth error to 0 at 1200 second so this approve that NMPC implementation can effectively be used on nonlinear models with multi input and multi output.

Keywords — *AUV, tracking control, nonlinear system, MIMO system, Nonlinear Model Predictive Control*

INTRODUCTION

Almost all the existing plant is a nonlinear system. The stability of the nonlinear system is one of the problems that can resolved to make the controlled system. Nonlinearity effect unwanted on the system. Thus, it is necessary for the controller design nonlinear system which has the ability to compensate that effect.

In previous studies, it is written it is written that to maintain depth performed with increasingly slow motion pitch. If the actual speed in flight mode in AUV reduced to minimum speed, then AUV can not control themselves. To overcome this required AUV design by adding a fixed wing (fixed wings) [2]. But the obstacles in using fixed-wing is the resistance which will be received by the AUV. Difficulties in the control system design problem of underwater vehicles because of its nonlinear dynamics, the model is indeterminate, and the emergence of disturbance that is difficult to be measured or estimated. Dynamics control of vehicle requires a guarantee of stability and perform consistently.

The difficulty of control system design problem on the dynamics of AUV is traditional linear design methodology can not be accommodated easily. Is fundamentally nonlinear dynamics in reality. Hydrodynamic coefficient is rarely known, and a variety of disturbances did not caused by a measurable flow [2]. The study, titled "Fault Tolerant Depth Control of the MARES AUV "take the nonlinear model MARES AUV dynamics parameters identified by using an augmented Kalman filter. The purpose of this study is heading error toward zero depth, but the simulation settings depth during normal operation indicates that the response is not stable.From some of the researches found the disadvantage of a nonlinear plant linearized causing narrowness of the working area. Appearance unmeasured disturbances caused by the currents can affect the performance of the system on the AUV. Setting the depth of the MARES AUV do not follow the references given and the pitch angle is unstable.

2. MARES AUV MODEL

The dynamic characteristics of the following autonomous underwater vehicle MARES are taken from research conducted by Bruno Ferreira, Miguel Pinto, Anibal Matos, and Nuno Cruz entitled "Hydrodynamic modeling and motion limits of AUV MARES". Verical projection of MARS AUV is shown in Figure 1 and lateral projection shown in Figure 2.

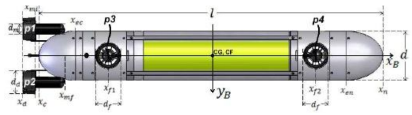

Fig. 1. Vertical Projection of MARES AUV [1]

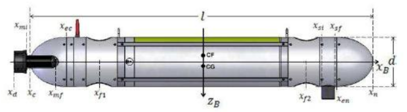

Fig. 2.Lateral Projection of MARES AUV [1]

TABLE 1.MARES AUV CHARACTERISTIC

Length	1.5 m
Diameter	20 cm
Weight in air	32 kg
Depth rating	100 m
Propulsion	2 horizontal + 2 vertical thruster
Horizontal velocity	0-1.5 m/s, variabel
Energy	Baterai Li-Ion, 600 Wh
Autonomy/Range	Sekitar 10 jam / 40 km

The model of MARES AUV considers all the main characteristics shown in Table 1. The derivative for the AUV dynamics model follows the standard approach shown in [8] which uses two reference frames: the Earth Fixed Frame (EFF) is assumed to have inertial properties and Body Fixed Frame (BFF) moving along with the vehicle. To connect linear and angular velocities as force and torque are defined into two frames, it is necessary to define the following,

$$\eta_1 = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \eta_2 = \begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix} \tag{1}$$

2

$$v_1 = \begin{bmatrix} u \\ v \\ w \end{bmatrix} \qquad v_{2\backslash} = \begin{bmatrix} p \\ q \\ r \end{bmatrix} \tag{2}$$

$$\tau_1 = \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \qquad \tau_2 = \begin{bmatrix} K \\ M \\ N \end{bmatrix} \tag{3}$$

Where η_1 and η_2 is the relative position and BFF orientation that refer to the inertial frame; v_1 and v_2 is the linear and angular velocity shown in the body frame coordinate; τ_1 and τ_2 is the force and torque applicable to the vehicle, also expressed in the body frame coordinates. Defined $\eta = [\eta_1^T \quad \eta_2^T], v = [v_1^T \quad v_2^T]$ and $J = diag(J_1, J_2)$ where,

$$J_1 = \begin{bmatrix} c\psi c\theta & -s\psi c\phi + c\psi s\theta s\phi & s\psi s\phi + c\psi s\theta c\phi \\ s\psi c\theta & c\psi c\phi + s\psi s\theta s\phi & -c\psi s\phi + s\psi s\theta c\phi \\ -s\theta & c\theta s\phi & c\theta c\phi \end{bmatrix} \tag{4}$$

$$J_2 = \begin{bmatrix} 1 & s\phi + t\theta & c\phi t\theta \\ 0 & c\phi & -s\phi \\ 0 & s\phi / c\theta & c\phi / c\theta \end{bmatrix} \tag{5}$$

The relationship between linear and angular velocities in the two frames is

$$\dot{\eta} = J(\eta_2)v. \tag{6}$$

Vehicle dynamic shown in BFF easily by

$$\tau_{ext} = M_{RB}\ddot{\eta} + C_{RB}(\dot{\eta})\dot{\eta}, \tag{7}$$

Where τ_{ext} is the compositional vector of the external force and the torque applicable to the vehicle, expressed in the body frame coordinates, M_{RB} is an inertial matrix and $C_{RB}(\dot{\eta})\dot{\eta}$ is a Coriolis and centripental matrix. External forces and moments can be decomposed as the sum of added mass, potential damping, drag, restoring, and propulsion,

$$\tau_{ext} = \tau_A + \tau_B + \tau_V + \tau_C + \tau_{prop} \tag{8}$$

3. THEORITICAL ANALYSIS

3.1 Vertical Plane Dynamics

The dynamics for this vertical motion are derived from the research of Bruno Ferreira [1]. Models that are reduced for vertical motion, considering that the cross-term can be eliminated:

$$M\dot{v} = -C(v)v - D(v)v - g(\eta_2) + P_f\, f_t(t) \tag{9}$$

Where,

$$v = \begin{bmatrix} u & w & q \end{bmatrix}^T \quad M = \begin{bmatrix} m - X_{\dot{u}} & 0 & -X_{\dot{q}} \\ 0 & m - Z_{\dot{w}} & -Z_{\dot{q}} \\ -M_{\dot{u}} & -M_{\dot{w}} & -M_{\dot{q}} \end{bmatrix},$$

$$C(v) = \begin{bmatrix} 0 & -mq & -Z_{\dot{w}}w - Z_{\dot{q}}q \\ -mq & 0 & X_{\dot{u}}u + X_{\dot{q}}q \\ Z_{\dot{w}}w + Z_{\dot{q}}q & -X_{\dot{u}}u - X_{\dot{q}}q & 0 \end{bmatrix}$$

,

$$D(v) = \begin{bmatrix} X_{|u|u}\,|u| & 0 & X_{|q|q}\,|q| \\ 0 & Z_{|w|w}\,|w| & Z_{|q|q}\,|q| \\ M_{|u|u}\,|u| & M_{|w|w}\,|w| & M_{|q|q}\,|q| \end{bmatrix},$$

$$g(\eta_2) = -\begin{bmatrix} (W - B)\sin\theta \\ (B - W)\cos\theta \\ -z_{CB}B\sin\theta \end{bmatrix},$$

$$P_f = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & x_{ts} & x_{tb} \end{bmatrix},$$

$$f_t(t) = \begin{bmatrix} f_p(t) \\ f_r(t) \\ f_s(t) \\ f_b(t) \end{bmatrix}$$

$f_t(t)$ is a force vector applied by a propellant generated according to the given control law, and, f_p, f_r, f_s and f_b is a scalar representing forces applicable to ports, starboard, stern, and bow thruster. It is assumed the force can be directly measured during operation. Inclusion of surge velocity is required in the reduced order of this model, because the non-negligible influence is owned by vertical plane dynamics.

3.2 Nonlinear Model Predictive Control

Nonlinear predictive control model (NMPC) is an optimization based on methods for nonlinear feedback control of nonlinear systems. The primary application is the problem of stabilization and tracking.

For example, a state-controlled process $x(n)$ measured during discrete $t_n, n = 0,1,2,....$"controlled" time means that each time can select a control input that affects future state system behavior. In tracking control, the task is to determine the control input $u(n)$ so that $x(n)$ follows the reference $x^{ref}(n)$. This means that if the current state is far from the reference then it is expected that the system settings redirect to the reference and if the current state is near the reference then it is expected the state remains that way.

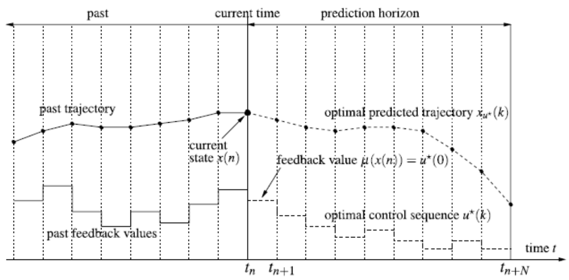

Fig. 3. NMPC Ilustration

Considered $x(n) \in X = R^d$ and $u(n) \in U = R^m$, subsequently considered the reference used is constant and equal $x_* = 0, i.e., x^{ref}(n) = x_* = 0$ to all $n \geq 0$. In order to provide a reaction for the present deviation $x(n)$ of the reference value $x_* = 0$, $u(n)$ is used in the form of feedback, which is in the form of $u(n) = \mu(x(n))$ some μ for mapping the state $x \in X$ into the settings U of the control values.
The idea of both linear and nonlinear predictive control models is to use the current process model in order to predict and optimize future system behavior. Used models in form

$$x^+ = f(x,u) \tag{10}$$

Which $f : X \times U \rightarrow X$ is a known and common nonlinear map providing state x and substitute state and control values u at a later time. Starting from the present state $x(n)$, for a given control sequence $u(0),...,u(N-1)$ with the length of the horizon $N \geq 2$, it can echo the equation (10) in order to construct a prediction trajectory defined as

$$x_u(0) = x(n),\ x_u(k+1) = f(x_u(k), u(k)),\ k = 0,....,N-1.$$

In this way, predictions $x_u(k)$ are obtained for the state of the system $x(n+k)$ at a time t_{n+k} in the future. Therefore, predictions of system behavior in discrete intervals $t_n,...,t_{n+N}$ depend on the selected control sequence $u(0),...,u(N-1)$.Then use the optimal controls in order to determine $u(0),...,u(N-1)$ which x_u is approaching $x_* = 0$. In the end, the calculated distance between $x_u(k)$ and $x_* = 0$ for $k = 0,...,N-1$ by function $\ell(x_u(k), u(k))$. Here, not only allows for the penalizing state deviation of the reference but also - if necessary - the distance of the control value $u(k)$ to the reference control u_*, which $u_* = 0$ is selected.
The common choice for this purpose is

$$\ell(x_u(k),u(k)) = \|x_u(k)\|^2 + \lambda\|u(k)\|^2 \quad (11)$$

Where $\|.\|$ is denoted as the usual Euclidean norm and $\lambda \geq 0$ is the weighting parameter for the control, which can be selected as 0. The current optimal control problem minimizes

$$J(x(n),u(.)) := \sum_{k=0}^{N-1} \ell(x_u(k),u(k))$$

With reference to all acceptable control sequences $u(0),...,u(N-1)$ with x_u generated from equation (10).It is assumed that the optimal control problem has a given solution by minimizing the control sequence $u*(0),...,u*(N-1)$, i.e.,

$$\min_{u(0),...,u(N-1)} J(x(n),u(.)) = \sum_{k=0}^{N-1} \ell(x_{u*}(k),u*(k)).$$

In order to obtain the desired feedback value $\mu(x(n))$, now set $\mu(x(n)) := u*(0)$, i.e., Applied the first element of the optimal control sequence. This procedure is shown in Figure 3.When $t_{n+1}, t_{n+2},...$ repeated procedures with new measurements $x(n+1), x(n+2),...$ in order to get feedback values $\mu(x(n+1)), \mu(x(n+2)),...$ In other words, we get feedback values μ with online optimization repeatedly exceeding the predictions generated by the model.The NMPC algorithm includes the family of optimal control strategies, in which cost functions are defined over the future horizon,

$$\Im(x,u) = \frac{1}{2}\int_0^{\tau_r} (y(t+\tau) - y_r(t+\tau))^T (y(t+\tau) - y_r(t+\tau))d\tau$$

Where τ_r is the prediction time, $y(t+\tau)$ a step τ precedes the prediction of the system output and $y_r(t+\tau)$ future reference trajectory. Weight control is not included in the cost function. However, control efforts can be obtained by determining prediction time.

The objective of the predictive control model is to calculate the control $u(t)$ in a way that the future plant's output $y(t+\tau)$ is moving closer with $y_r(t+\tau)$. This is solved by minimizing $\Im$.

SIMULATION

In this sub-section will be reduced non-linear model 6 DOF MARES AUV into 3 DOF in longitudinal model which can be used for speed, depth, and pitch setting. The controller will be implemented using speed control and position control in surge, heave and pitch.

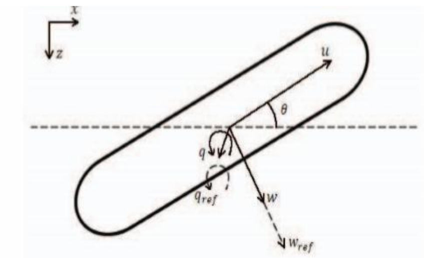

Fig. 4. BFF and EFF coordinates in longitudinal model [1]

The movement of the longitudinal model on MARES AUV is influenced by the Earth Fixed Frame (EFF) and Body Fixed Frame (BFF) shown in Figure 4. The translational motion of the longitudinal model is the surge motion which is denoted by showing the direction of translational motion on the axis and the heave motion denoted by indicating the direction of translational motion on the axis. The rotational motion of the longitudinal model is the pitch motion denoted by indicating the direction of the rotational motion on the axis. In this paper, AUV is expected to move at a constant speed.

The result of motion simulation at the depth of MARES AUV without controller is shown in Figure 6, and the result of motion simulation at the depth control using NMPC is shown in Figure 7. It is seen that the response follows the given trajectory.

Algorithm that be used in this research is algorithm NMPC for time varying reference x^{ref} with posteriori suboptimality estimation, this algorithm also used in (19) i.e:

Set $\alpha = 1$, at each time sampling $t_n, n = 0,1,2,...$:

1. Find the state system $x(n) \in X$
2. set $x_0 = x(n)$ and optimal control problem:

Minimalize $J_N(n, x_0, u(\cdot)) := \sum_{k=0}^{N-1} \ell(n+k, x_u(k, x_0), u(k)$

According to $u(\cdot) \in U^N(x_0)$, subject to

$$x_u(0, x_0) = x_0,\ x_u(k+1, x_0) = f(x_u(k, x_0), u(k)) \quad (12)$$

With optimal control sequence $u^*(\cdot) \in U^N(x_0)$.

3. Find the feedback value NMPC $\mu_N(n, x(n)) := u^*(0) \in U$ and use that value for next sampling
4. if $n \geq 1$ find α :

$$\alpha_l = \frac{V_N(n-1, x(n-1)) - V_N(n, x(n))}{\ell(n-1, x(n-1), \mu_N(n-1, x(n-1)))},$$
$$\alpha = \min\{\alpha, \alpha_l\}$$

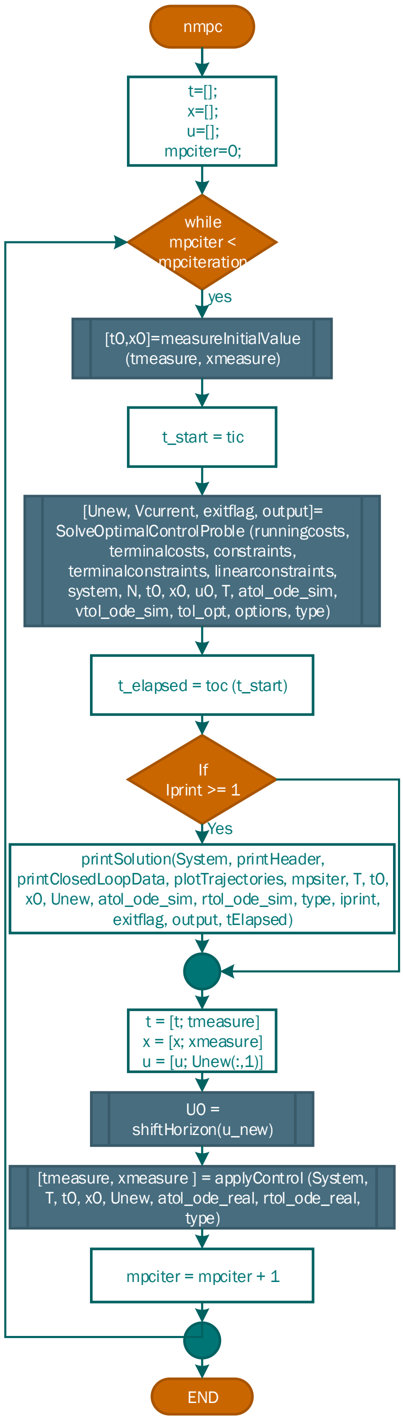

Fig. 5. Flowchart of NMPC Simulation procedure

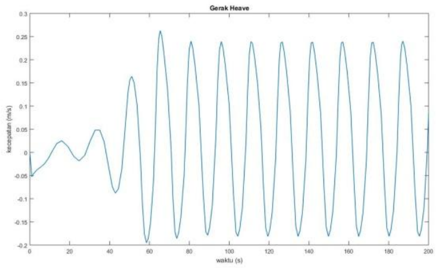

Fig. 6. Simulation result for heave velocity without controller

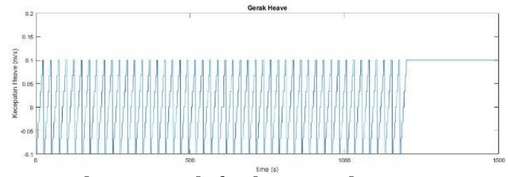

Fig. 7. Simulation result for heave velocity using NMPC

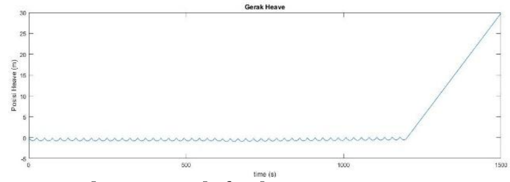

Fig. 8. Simulation result for heave position using NMPC

CONCLUSION

This paper shows the NMPC control strategy used for motion control of AUV with constant current effects. Nonlinear model of MARES AUV is reduced to 3 DOF to define the error dynamics model. The model is used by the NMPC algorithm for get the output value corresponding to the given reference. The simulation results shows that the proposed NMPC implementation can lead to a depth error leading to 0 at 1200 seconds, thus proved that NMPC can effectively be used in nonlinear models with multi input and multi output.

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