Clonal Selection Algorithms for 6-DOF PID Control of Autonomous Underwater Vehicles

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Abstract. Autonomous underwater vehicles(AUVs) have been drawing increasing interests in various marine applications such as coastal structure inspection, sea floor exploration, and oceanographic monitoring. Due to the complexity of underwater stream dynamics and the prevalence of unexpected underwater obstacles, it is imperative to develop self-adjustable, intelligent navigation control functions for AUVs. Among various control techniques, we focus on the proportional-integral-derivative(PID) controller since it is still one of the dominant techniques in actual underwater vehicle control systems. We propose to apply the Clonal Selection Algorithm to determine optimal combination of three gain coefficients, K_P, K_D, K_I of the PID controller. Our simulation shows that the proposed technique provides better responses than the existing Ziegler-Nichols technique with respect to the settling time, overshoot and an affinity in submerging under water and turning the yaw angle through simulation. We expect that AUVs could autonomously regulate three coefficients of six degree-of-freedom(DOF) PID controllers through real-time onboard processing.

Keywords: Autonomous Underwater Vehicles, 6-DOF PID controller, Clonal Selection Algorithms (CSA), Ziegler-Nichols technique.

1 Introduction

Autonomous underwater vehicles(AUVs) have become an important tool for various underwater tasks because they have greater speed, endurance, and depth capability as well as a higher factor of safety than human divers. However, most vehicle control system designs have been based on a simplified vehicle model, which has often resulted in poor performance because the nonlinear and time-varying vehicle dynamics have coefficient uncertainty. It is desirable to have an advanced control system with the capability of learning and adapting to changes in the vehicle dynamics and parameters [1]. Thus, AUVs need the autonomous coefficient tuning due to the complexity of underwater stream dynamics and the prevalence of unexpected underwater obstacles. There have been a few advanced control techniques of AUVs. Autonomous diving and steering of unmanned underwater vehicles can be controlled by multivariable sliding mode control [2]. Discrete-time Quasi-sliding

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mode systems have been adapted for control of autonomous underwater vehicles [3]. Recently, the revised precision controller is tested through model parameters optimization using the Nelder-Mead Simplex Technique [4]. Although a few control techniques have been suggested, they have some difficulties to apply autonomous underwater vehicles. We utilize the classical control technique which is the PID controller to determine the attitude and position of AUVs. They have been successfully applied to many different problems in control fields and have achieved valuable results [5]. Basically, the classical Ziegler-Nichols technique has been used for tuning PID controllers [6]. The modified Ziegler-Nichols technique has been suggested to improve the performance and efficiency of the classical Ziegler-Nichols technique [7]. Recently, the PID neural network is used for the temperature control system [8]. The purpose of this work is to ascertain the effect of using Clonal Selection Algorithms for 6-DOF PID controllers of AUVs.

2 Dynamic for 6-DOF of Autonomous Underwater Vehicles

For Autonomous Underwater Vehicles(AUVs) in 6 Degrees of Freedom(DOF) the dynamic equations of motion are usually separated into the translational and rotational motions. The position is specified by three vectors which are surge, sway and heave. On the other hand various representations of an attitude have been discussed. Between them, the most frequently applied representations of it are Euler angle conventions which are minimal three parameter representations. The roll, pitch and yaw convention dominate in the context of mobile vehicles [9]. There are significant coupling problems between the rotational and translational motion for the 6 DOF underwater vehicles control. Therefore, several mathematical models have been proposed to solve these problems. Among them, we used underwater robotic vehicle dynamics model proposed by T. I. Fossen, 1994 [10]. It contains kinematic equations of motion, rigid-body dynamics, added inertia, hydrodynamic damping, and restoring forces.

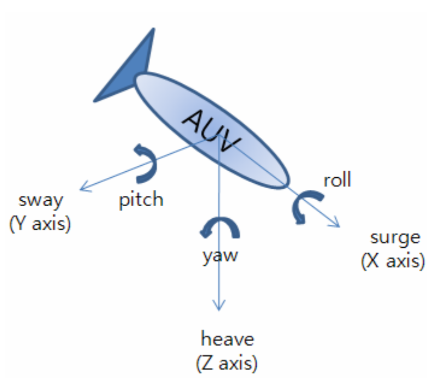

Fig. 1. Body fixed coordinate system and 6-DOF of AUVs

3 6-DOF PID Controllers of AUVs Applied Clonal Selection Algorithms

3.1 PID Controllers

A proportional-integral-derivative(PID) controller is a general feedback loop component in control systems. Each coefficient of a PID controller works three common requirements of control problems. The proportional part works to handle an immediate error, the error is multiplied by a constant(K_P). The integral part works to learn from the past, the error is integrated and multiplied by a constant(K_I). The derivative part works to predict the future, the first derivative is calculated and multiplied by a constant(K_D). The PID controller can change outputs adequately based on the history and rate of change of the error, which gives more accurate and stable systems.

Table 1. The effect of increasing coefficients

	Rise time	Overshoot	Settling time
K_P	Decrease	Increase	Small change
K_I	Decrease	Increase	Increase
K_D	Small change	Decrease	Decrease

3.2 Rigid Body Dynamics of AUVs

Newton's equations of the motion for rigid-body with constant mass are written [11]:

$$m[\dot{u} - vr + wq - x_G(q^2 + r^2) + y_G(pq - \dot{r}) + z_G(pr + \dot{q})] = \sum X . \tag{1}$$

$$m[\dot{v} - ur + wp - y_G(r^2 + p^2) + z_G(qr - \dot{p}) + x_G(qp + \dot{r})] = \sum Y . \tag{2}$$

$$m[\dot{w} - wq + vp - z_G(p^2 + q^2) + y_{xG}(rp - \dot{q}) + y_G(rq + \dot{p})] = \sum Z . \tag{3}$$

$$I_x \dot{p} + (I_x - I_y)qr - mz_G(\dot{v} + ur - wp) = \sum K . \tag{4}$$

$$I_x \dot{q} + (I_x - I_z)pr + m[z_G(\dot{u} - vr + wp) - x_G(\dot{w} - wq + vp)] = \sum M . \tag{5}$$

$$I_x \dot{r} + (I_y - I_x)pq + mx_G(\dot{v} - wp + ur) = \sum N . \tag{6}$$

where x_G, y_G, z_G is the center of gravity, m is the constant mass, I_x, I_y, I_z is the inertia matrix of AUVs, $\upsilon^B = [u, v, w]^T$ is the velocity of the origin of body axis relative to fluid, $\omega^B = [p, q, r]^T$ is the angular velocity component about each axis relative to fluid, X, Y, Z and K, M, N are vectors of external applied forces and moments, respectively.

3.3 6-DOF PID Controllers for AUVs

The closed-loop system is guaranteed by using standard stability analysis [12]. The error is calculated as the difference between the actual distance, Euler angle and target distance, Euler angle.

$$\tilde{\varepsilon} = \varepsilon_a - \varepsilon_T \,. \tag{7}$$

$$s = K_P \tilde{\varepsilon} + K_D \dot{\tilde{\varepsilon}} + K_I \int_{t_0}^{t} \tilde{\varepsilon}(\tau) d\tau \,. \tag{8}$$

where K_P, K_D, K_I are gain coefficients and $\varepsilon_a, \varepsilon_T$ is the actual distance, Euler angle and the target distance, Euler angle. According to gain coefficients, the system responds differently. We calculate moderate K_P, K_D, K_I gain coefficients by using the classical Ziegler-Nichols technique.

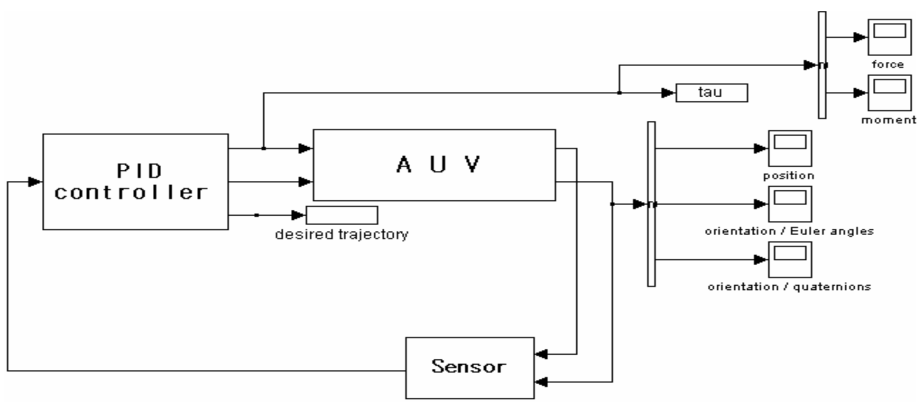

Fig. 2. Block diagram of the 6-DOF PID controller

3.4 Clonal Selection Algorithms for Tuning PID Controller of AUVs

The immune system is capable of learning, memory, and pattern recognition. By employing genetic operators on a time scale fast enough to observe experimentally, the immune system is able to recognize novel shapes without preprogramming [13].

Artificial immune systems(AIS) use ideas gleaned from immunology in order to develop adaptive systems capable of performing a wide range of tasks in various areas of research. The general algorithm, named CLONALG, is derived primarily to perform machine-learning and pattern-recognition tasks and then it is adapted to solve optimization problems, emphasizing multimodal and combinatorial optimization [13]. The Clonal Selection Algorithm(CSA) is based on the artificial immune system. The CSA is used in the field of optimization and pattern recognition [15].

The movement of AUVs can be optimally controlled by selecting its PID gain coefficients. Usually, the gain coefficients for the PID controller are measured by empirical experiments. Therefore, it is appropriate to apply the CSA to get the optimal gain coefficients. First, generate a population of PID gain values randomly and compute all the affinity values for that. The affinity measures are computed by the equation (9). After that, the select gain values with high affinity. And then, they are identically copied, and mutated with high rates. These are replaced with the gain values in the initial population which have lower affinity. These processes are iteratively performed until CSA gives converged, optimal gains. Finally, all PID gain coefficients are optimally selected by CSA. This allows the control system of AUVs to operate without high-overshoot or longer-settling time.

$$Affinity = \frac{1}{1 + error}. \tag{9}$$

$$Error = \sum_{i=1}^{n} \left| A_i - T_i \right|. \tag{10}$$

A_i : The actual distance and Euler angle against each axis(x, y, z),

T_i : The target distance and Euler angle against each axis(x, y, z)

4 Simulation Position and Attitude of AUVs

We determined some parameters and surroundings for simulation.

- **Weight of the AUVs : 120 kg**
- **Shape of the AUVs : Sphere type with six thrusters for 6 DOF**
- **Buoyancy : Neutral / Place : An indoor swimming pool**
- **Target depth : 5 meters, Target yaw angle : 90 degree**
- **Population size : 50 / Clone per antibody : 6**
- **Generation : 30 / Number of bits : 16**
- **Hypermutation rate : 0.05**
- **Simulation time : 120(s) for depth control, 30(s) for yaw angle control**

4.1 Experiment 1. The Depth Control of AUVs

The first simulation is to keep 5 meters under water. We do not need to consider an external force because we assume the place an indoor swimming pool. Results are compared to the classical Z-N technique.

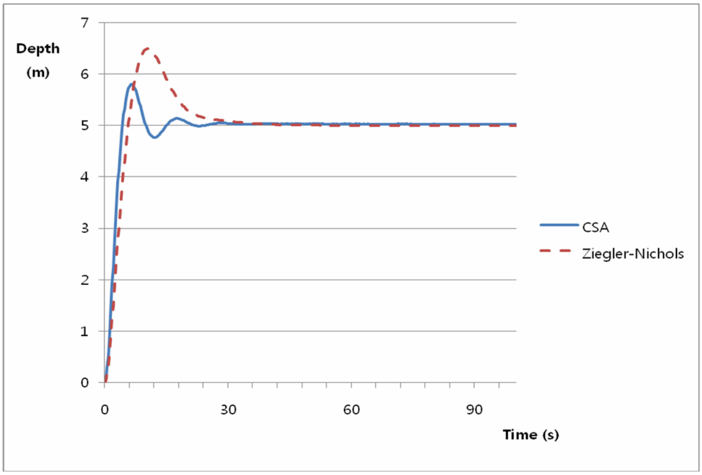

Fig. 3. The depth control of AUVs between CSA and classical Z-N technique

We know that proportional coefficient K_P and derivative coefficient K_D are larger than the integral coefficient K_I. Although the CSA has larger K_P coefficient, the overshoot is less than the classical Z-N technique.

Table 2. The comparison of PID controller efficiency for depth control of AUVs

	Classical Ziegler-Nichols	Clonal Selection Algorithm
K_P	41.7	65.53
K_I	4.04	0.12
K_D	107.37	65.50
Maximum overshoot	6.5 (m)	5.8 (m)
settling time	28.4 (s)	19.2 (s)
affinity	0.0064	0.0110

4.2 Experiment 2. The Yaw Angle Control of AUVs

The second simulation is turning 90 degrees the yaw angle while AUVs keep the depth under water. Similar to the experiment 1, we assume that the external force does not exist.

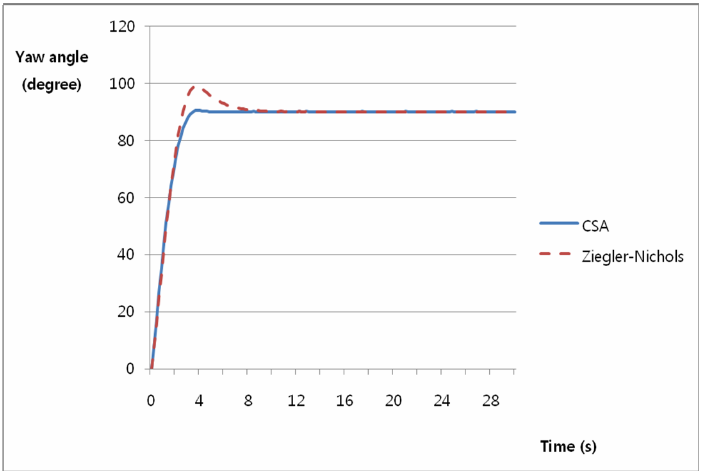

Fig. 4. The yaw angle control of AUVs between CSA and classical Z-N technique

Compared to the experiment 1, the settling time is reduced. It means that the PID controller has the different gain according to the 6 DOF of the AUVs. Thus, we have to check each coefficient K_P, K_D, K_I through the previous simulation.

Table 3. The comparison of PID controller efficiency for yaw angle control of AUVs

	Classical Ziegler-Nichols	Clonal Selection Algorithm
K_P	61	65.53
K_I	43.5	0.018
K_D	21.57	0.005
Maximum overshoot	99.1 (degree)	90.1 (degree)
settling time	7.8 (s)	4.8 (s)
affinity	0.0014	0.0017

5 Discussion

In the experiment 1, we easily find that the settling time of the CSA is shorter than the classical Z-N technique. The overshoot of the CSA is less than the classical Z-N technique. As the proportional coefficient K_P and the integral coefficient K_I increase, the overshoot of the response is decreased. However, the overshoot of the response is increased as the derivative coefficient K_D increase. This means that each coefficient of the PID controller gain K_P, K_I, K_D is mutually affected to the response. In addition, the affinity of the CSA is approximately two times comparing to the classical Z-N technique. As a result, we know that CSA is the more efficient technique and guarantees the excellent performance. In addition, results of the experiment 2 are similar comparing to those of the experiment 1. The settling time of CSA is shorter than the classical Z-N technique and the overshoot of CSA is less than the classical Z-N technique. On the other hand, the affinity of the CSA is similar to the Z-N technique.

We assume the place an indoor swimming pool. However, AUVs are utilized to navigate under sea. They could encounter unpredictable situations and be affected the density of water and the current along the depth of water. Thus, they should easily change PID coefficients along situations to enhance performance. AUVs have the threshold of settling time, overshoot and affinity of PID controller. If they exceed the threshold value, AUVs could recalculate PID coefficients based on their trace.

We should consider many factors in developing AUVs with mechanical and electrical views. For example, the external hull is important because buoyancy is different along with the body shape. After AUVs are made, we test them through the simulation to maximize the performance and efficiency of AUVs. First of all, attitude and position control of AUVs are important to execute their missions. Thus, we could get a valuable improvement of AUVs through simulation.

6 Conclusion

It is important to keep the body of AUVs stable during missions. Several technicians have suggested control systems for AUVs control. Among them, we adapt the classical control technique PID controller. Our present study evaluates the performance and efficiency of 6-DOF PID controllers through the CSA comparing to the classical Z-N technique. We verify that the CSA is more efficient than the Z-N technique in submerging and turning yaw angle through the simulation. We expect that AUVs could autonomously regulate three coefficients of six degree-of-freedom (DOF) PID controllers through real-time onboard processing for undersea exploration.

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