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COMPARISON OF TWO METHODS LQR, SDRE FOR THE ROBOT SUBMARINE

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ABSTRACT

In this paper we want to introduction the underwater robot and compare the ROV(remotely operated vehicles) and AUV (autonomous underwater vehicles). The control issue of underwater robots is very challenging due to the nonlinearity, time variance, unpredictable external disturbances, such as the sea current fluctuation, and the difficulty in accurately modeling the hydrodynamic effect. For this issue we by use of two methods, LQR & SDRE want to optimize operation of the robot submarine, comparison two methods will be done and behavior of system after applying LQR & SDRE will draw during the paper. Numerical simulations are given to illustrate the effectiveness and validity of the proposed approach.

Key words: Underwater robot; Robot submarine; Optimize operation; LQR; SDRE.

1- INTRODUCTION

Oceans are the main resource of the energy and chemical balance that sustains mankind whose future is very much dependent on the living and nonliving resources in the oceans [1]. Oceans' activities are also critically relevant to climate changes. Therefore, various studies have been conducted for ocean exploration and intervention. Underwater vehicles have been a popular and effective means for ocean exploration and intervention as they make it possible to go far beneath the ocean surface, collect first-hand information about how the oceans work, and furthermore perform intervention tasks.

There are three types of underwater vehicles. 1) Manned submersible vehicles: They can carry out complicated tasks because of human intelligence. However, they have short endurance due to human physical and psychological limitations, and are costly to operate because of the endeavor done to ensure human safety. Alvin at the Woods Hole Oceanographic Institute and Pisces V at the NOAA Hawaii's Undersea Research Laboratory are examples of manned submersible vehicles. 2) Remotely operated vehicles (ROV): They are unmanned, tethered vehicles with umbilical cables to transfer power, sensor data and control commands between the operators on the surface and the ROV. They are usually launched from surface ships. They can also carry out complicated tasks via tele-operation by human pilots on the surface ships. Even though their operations are often limited by operator fatigue, they are free from the safety concern of on-board human operators and have almost unlimited endurance in the ocean, compared to manned submersibles. However, the dragging force on the tether, time delay, and operator fatigue make ROV difficult to operate and the daily operating cost is still very expensive. KAIKO from the Japanese Marine–Earth Science and Technology Center (JAMSTEC) was the most advanced ROV ever operated at a 11 000-m depth. Unfortunately, KAIKO was lost during the operation in 2003 as the tether was snapped due to bad weather.

3) Autonomous underwater vehicles (AUVs) or underwater robots: They are unmanned, tether-free, powered by onboard energy sources, equipped with various navigation sensors such as inertial measurement unit (IMU), sonar sensor, laser ranger, and pressure sensor, and controlled by onboard computers for given missions. They are more mobile and could have much wider reachable scope than ROV. On-board power and intelligence could help AUV self-react properly to changes in the system and its environment, avoiding any disastrous situation like the KAIKO case. With the continuous advance in control, navigation, artificial intelligence, material science, computer, sensor, and communication, AUVs have become a very attractive platform in exploring the oceans, and numerous AUV prototypes have been

proposed, such as ODIN [2], REMUS [3], and ODYSSEY [4]. While most of the currently available AUV are for noncontact tasks such as mapping, monitoring or sampling in the water column, research on AUV with robotic manipulators has recently been underway [5]. Various underwater robotic technologies were surveyed by Yuh and West [6].

The control issue of AUV is very challenging due to the nonlinearity, time-variance, unpredictable external disturbances, such as the environmental force generated by the sea current fluctuation, and the difficulty in accurately modeling the hydrodynamic effect. The well-developed linear controllers may fail in satisfying performance requirements especially when changes in the system and environment occur during the AUV operation since it is almost impossible to manually retune the control parameters in water. Therefore, it is highly desirable to have an AUV controller capable of self-adjusting control parameters when the overall performance degrades. Various advanced control schemes for underwater robots have been proposed in the literature as some of them are summarized below:

Sliding mode control (SMC): SMC restricts the system states inside a certain subspace of the whole state space and makes them asymptotically converge to their equilibrium point. It requires a raw estimation of the system parameters and an estimation of the system uncertainty for the switching surface design and variable-structure control lawdesign. Even thoughSMChas been well known for its robustness to parameter variations, it has the inherent problem of chattering phenomenon. Yoerger and Newman [7] and Yoerger and Slotine [8] introduced the basic methodology of using sliding mode control for AUV application, and later Yoerger and Slotine [9] developed an adaptive sliding mode control scheme, in which a nonlinear system model was used. When the generalized disturbance makes the system state exceed the sliding mode tolerance layer, the exceeding value is used to update the nonlinear model parameters and furthermore update the control input. Song and Smith [10] introduced a sliding mode fuzzy controller that uses Pontryagin’s maximum principle for time-optimal switching surface design, and uses fuzzy logic to form this surface.

Robust/optimal control: The principles of the robust/optimal control are calculus of variations, Pontryagin maximum principle, and Bellman dynamic programming. However, due to the difficulty of deriving an accurate model of AUV system, it is difficult to apply optimal control directly. Therefore, generally optimal control combined with system identification or robust control is used in AUV control. Kim *et al.* [11] proposed an H_2/H_∞ control scheme, in which the robust stability problem against time delays and parameter uncertainties is transformed into H_∞ control problem, and performance problem is transformed into H_2 problem. Riedel and Healey [12] proposed an optimal control (LQR) scheme that uses an auto-regression (AR) model to predict the wave-induced hydrodynamic disturbance. Adaptive control: Adaptive control modifies control gains according to the changes in the process dynamics and the disturbances. Since there are parameter uncertainties and unknown disturbances in the underwater vehicle’s hydrodynamics, many researchers studied adaptive control to address the AUV control issues. However, adaptive control may fail when the dynamics changing speed is beyond its adapting capability, and the model-based adaptive control may be calculation burdensome because of the excessive endeavor in system identification. Cristi and Healey [13] proposed a model-based adaptive controller. Assuming that the vehicle dynamics are nearly linear within the range of its operating conditions, the controller uses the RLS method for system parameter estimation and, futhermore, uses the pole placement technique for control gain desgin. Yuh [14] proposed a discrete-time adaptive controller using a parameter adaptation algorithm. Yuh [15], and Yuh and Nie [16] proposed a nonregressor-based adaptive control scheme that uses parametric bound estimation, instead of system parameter estimation, to tune the control gains.

Neural network (NN) control: Neural networks attracted many researchers because they can achieve nonlinear mapping. Using NN in constructing controllers has the advantage that the dynamics of the controlled system need not be completely known. This makes NN suitable for underwater vehicle control. However, NN-based controllers have the disadvantage that no formal mathematical characterization exists for the closed-loop system behavior. The validation of the final design can only be demonstrated experimentally. There are mainly two approaches in using NN for control purpose: learning with a forward model and direct learning. In the former approach, generally, the forward model is trained by the output error or state error and then used for gain derivation, while in the latter approach, the state or output error is used directly to map the desired control input [17]. Yuh [18] described a multiplayer feedforward network.

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Each layer has 13 neurons, except the last layer that has six neurons. The input signals are six position errors, six velocity errors and a constant. The output signals are the six control forces. The back-propagation (BP) algorithm is used for training the network. Ishii *et al.* [19] proposed a neural network system that is based on self-organizing neural-net control system (SONCS) that executes identification of robot dynamics and controller adaptation in parallel with robot control and adjusts the controller network based on the results of virtual operation of the control calculation and the actual control operation.

Fuzzy logic control: The theoretical basis of fuzzy logic control is that any real continuous function over a compact set can be approximated to any degree of accuracy by the fuzzy inference system. For control engineering applications, researchers use fuzzy logic to form a smooth approximation of a nonlinear mapping from system input space to system output space. This makes it suitable for nonlinear system control. However, determining the linguistic rules and the membership functions requires experimental data and, therefore, very time-consuming, and the rule-based structure of fuzzy logic control makes it difficult to characterize the behavior of the closed-loop system in order to determine response time and stability. Kato *et al.* [20] used a very basic fuzzy controller in AQUA EXPLORER 1000 cable inspection. Lee *et al.* [21] proposed a self-adaptive neurofuzzy inference system (SANFIS) that uses a five-layer-structured NN to achieve better function approximation: a recursive least squares algorithm and a modified Levenberg–Marquardt algorithm with limited memory are used in extracting fuzzy rules and tuning the membership functions. Kim and Yuh [22] proposed a fuzzy membership function-based neural network (FMFNNs) that uses a BP network for fuzzy control's membership function derivation. This paper will describe ROV and AUV and by use of two methods LQR and SDRE will control this system and will show different between two methods.

2- ROV(REMOTELY OPERATED VEHICLES)

A remotely operated underwater vehicle, commonly referred to as an ROV, is a tethered underwater vehicle. They are common in deep water industries such as offshore hydrocarbon extraction. While the traditional abbreviation "ROV" stands for remotely operated vehicle, one must distinguish it from remote control vehicles operating on land or in the air. ROVs are unoccupied, highly maneuverable, and operated by a crew aboard a vessel. They are linked to the ship by either a neutrally buoyant tether or, often when working in rough conditions or in deeper water, a load-carrying umbilical cable is used along with a tether management system (TMS). The TMS is either a garage-like device which contains the ROV during lowering through the splash zone or, on larger work-class ROVs, a separate assembly which sits on top of the ROV. The purpose of the TMS is to lengthen and shorten the tether so the effect of cable drag where there are underwater currents is minimized. The umbilical cable is an armored cable that contains a group of electrical conductors and fiber optics that carry electrical power, video, and data signals between the operator and the TMS. Where used, the TMS then relays the signals and power for the ROV down the tether cable. Once at the ROV, the electrical power is distributed between the components of the ROV. However, in high-power applications, most of the electrical power drives a high-power electrical motor which drives a hydraulic pump. The hydraulic pump is then used for propulsion and to power equipment such as torque tools and manipulator arms where electrical motors would be too difficult to implement subsea. Most ROVs are equipped with at least a video camera and lights. Additional equipment is commonly added to expand the vehicle's capabilities. These may include sonars, magnetometers, a still camera, a manipulator or cutting arm, water samplers, and instruments that measure water clarity, water temperature, water density, sound velocity, light penetration, and temperature.

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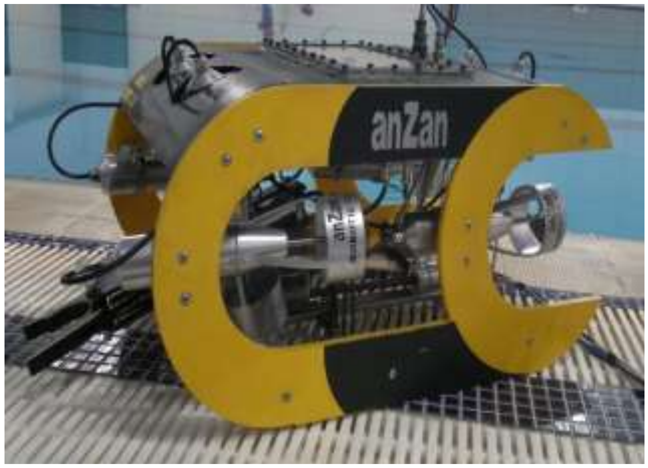

Fig.1. ROV robot

3- AUV (AUTONOMOUS UNDERWATER VEHICLES)

An autonomous underwater vehicle (AUV) is a robot which travels underwater without requiring input from an operator. The first AUV was developed at the Applied Physics Laboratory at the University of Washington as early as 1957 by Stan Murphy, Bob Francois and later on, Terry Ewart. The "Special Purpose Underwater Research Vehicle", or SPURV, was used to study diffusion, acoustic transmission, and submarine wakes. Other early AUVs were developed at the Massachusetts Institute of Technology in the 1970s. One of these is on display in the Hart Nautical Gallery in MIT. At the same time, AUVs were also developed in the Soviet Union (although this was not commonly known until much later).

AUVs constitute part of a larger group of undersea systems known as unmanned underwater vehicles, a classification that includes non-autonomous remotely operated underwater vehicles (ROVs) – controlled and powered from the surface by an operator/pilot via an umbilical or using remote control. In military applications AUVs are more often referred to simply as unmanned undersea vehicles (UUVs).

Fig.2. AUV robot

4- DYNAMIC MODEL

The dynamic model uses the orthogonal coordinate systems: global coordinate system, *(0*,I, ***J*** **,** *K*), which remains fixed at the ocean surface (mother ship) with origin 0, *K* pointing down into the water normal to the surface and I and J chosen in any two convenient mutually perpendicular horizontal directions with the only restriction being that the axes form- a right-handed system; and a local coordinate system, (P,i, j, ***k***

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) , which **is** fixed on the vehicle with origin at *P*,*i* pointing through the nose ***of*** the vehicle, ***k*** pointing through the belly of the vehicle and *j* completing the right-handed system. The position and orientation of the vehicle in global Coordinates can be specified by *R*,, the vector from 0 to *P*, and the Euler angles ***+,O,b.*** Transformation of forces and motions from local to global coordinates can be accomplished by using the transformation matrix [T] and from global to local by using its inverse (which is just *[T]*^{T} since *[T]* is an orthogonal matrix) where:

$$[T] = \begin{bmatrix} \cos\psi\cos\theta & \cos\psi\sin\theta\sin\phi - \sin\psi\cos\phi & \cos\psi\sin\theta\cos\phi + \sin\psi\sin\phi \\ \sin\psi\cos\theta & \sin\psi\sin\theta\sin\phi - \cos\psi\cos\phi & \sin\psi\sin\theta\cos\phi - \cos\psi\sin\phi \\ -\sin\theta & \cos\theta\sin\phi & \cos\theta\sin\phi \end{bmatrix}$$

The development of the dynamic model is carried out in the local Coordinate system since the motion of the vehicle is usually described in reference to this system.

The equation motion of this system is:

$$M(\dot{v}) + C(v) + D(v)v + g(\eta) = \tau$$

$$\dot{\eta} = J(\eta)v$$

$$M_\eta(\eta)\ddot{\eta} + C_\eta(v,\eta)\dot{\eta} + D_\eta(v,\eta)\dot{\eta} + g_\eta(\eta) = \tau_\eta$$

5- SIMULATION RESULTS

In this section, simulation results using MATLAB for the depth control are presented. For the purpose of illustration, computer simulation is done for the REMUS (Remote Environmental Unit) AUV [23]. REMUS is a low-cost, modular vehicle with applications in autonomous docking, long-range oceanographic survey, and shallow-water mine reconnaissance. The parameters of the dive plane model of the REMUS are collected in the Appendix. Here for the purpose of comparison, simulations are done using the controllers designed for the constrained as well as unconstrained fin angle. The performance of the optimal control systems depends on the choice of the weighting matrices in the performance index.

A) LQR algorithm

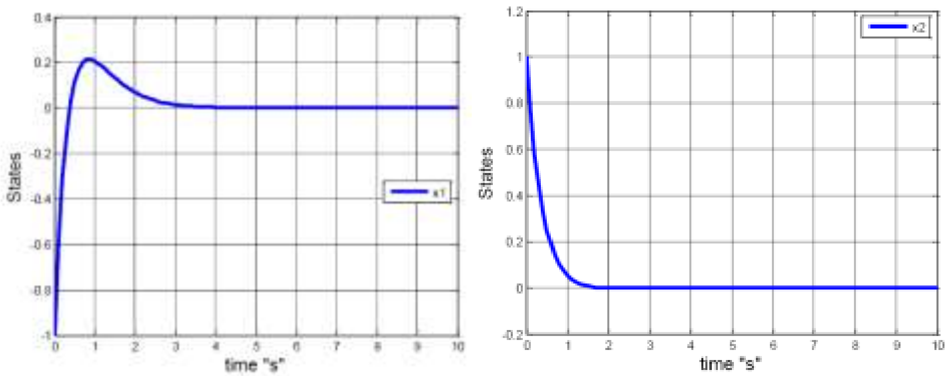

Fig. 3. Behavior of system in LQR algorithm

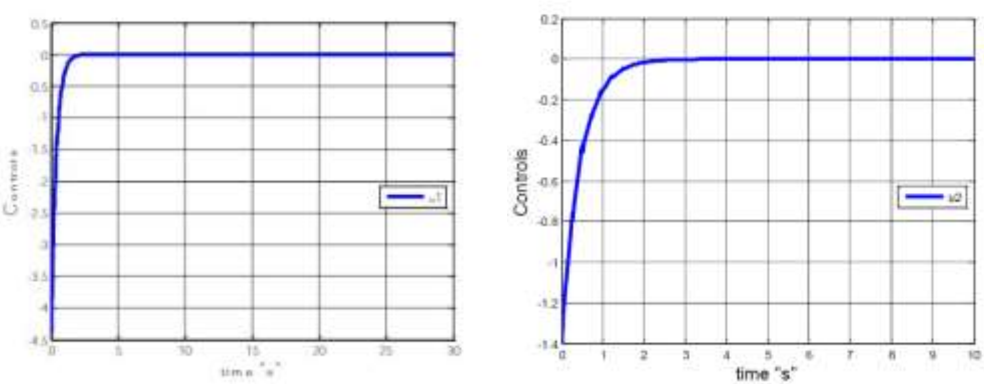

Fig. 4. Behavior of controller in LQR algorithm

B) *SDRE algorithm*

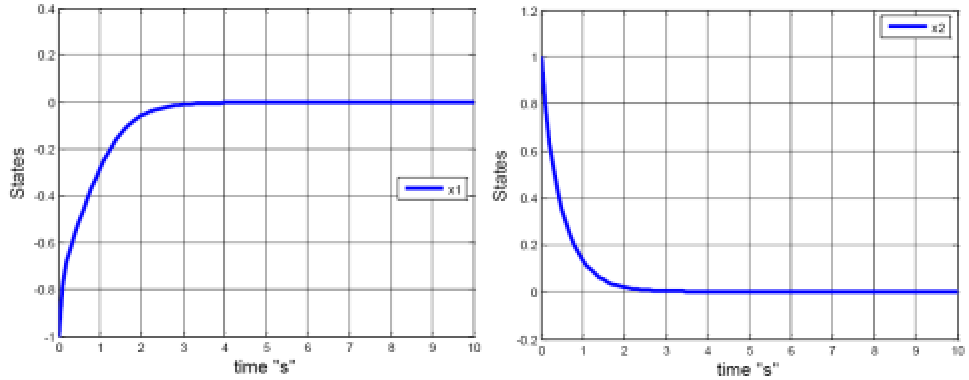

Fig. 5. Behavior of system in SDRE algorithm

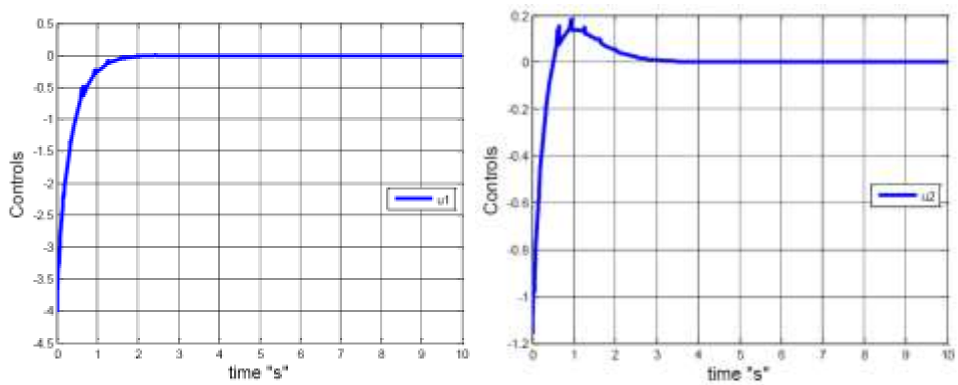

Fig. 6. Behavior of controller in SDRE algorithm

6- CONCLUSION

In this paper we introduced ROV (remotely operated vehicles) and AUV (autonomous underwater vehicles) and by two methods we controlled the robot in the general mode at the final step we simulated behavior of system and saw amount effect of SDRE and LQR methods, per two methods has almost the same equations but the difference was in two A & B matrixes that in LQR method was fixed but in SDRE was variable in per step. In general conclusion we can say two methods are suitable and the engineers should chose his methods depend on problems.

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