Identification and Control of the Phantom 500 Body Motion

Jean-Pierre Folcher and Maria-João Rendas
Laboratoire d'Informatique, Signaux et Systèmes de Sophia Antipolis (I3S)
2000 route des Lucioles, BP 121, 06509 Sophia Antipolis Cedex, France
e-mail: {folcher,rendas}@i3s.unice.fr

Abstract- **This paper addresses the identification and the control of the vertical motion of the ROV Phantom. The problems are split in two decoupled problems : the propeller motion and the diving motion. A maximum likelihood based identification method is used for each dynamic model. The design of the inner and outer controllers is based on the classical root locus method. Numerical experiments demonstrate that the designed controllers yield satisfactory results in terms of stability, tracking performance and robustness.**

I INTRODUCTION

In September 1998 the European Long Term Research project NARVAL *(Navigation of Autonomous Robots via Active Environmental Perception*) started development of an architecture to support studies on AUV control and based on the Remotely Operated Vehicle (ROV) Phantom 500,[1] see Fig. 1.

The paper presents work of *the Laboratoire d'Informatique, Signaux et Systèmes de Sophia Antipolis* (I3S) concerning the design of the low-level control system. The main objective of this system is to ensure closed loop performance such as stability, tracking, and perturbation rejection in the horizontal and vertical planes. Since the vehicle is equipped with only one vertical and two horizontal thrusters, the number of degree of freedom is smaller than the number of actuators. A common pragmatic approach (see, e.g., [5]) consists in designing three decoupled or slightly coupled controllers : for longitudinal speed motion, for diving motion and for steering motion.

Each controller is designed applying Root Locus techniques to identified dynamic models. These body motion controllers are used in conjunction with higher level controllers for the guidance of the vehicle (see for instance the companion paper [3] where an algorithm for guidance along sea-bed boundaries using vision is presented).

The organization of the paper is the following. We first briefly present the ROV Phantom and the set of sensors installed on the platform. In the subsequent section we assess the design of rotation speed controllers for the ROV thrusters. Section IV is dedicated to the control of the vertical motion. In each of these sections, the parametric dynamic model is presented, its identification discussed, and finally, the corresponding controller is designed. A final section presents conclusions and perspectives for future evolutions.

II THE ROV PHANTOM 500

The Phantom 500 vehicle has an open frame structure (see Fig.1) and is 1 meter long, 0.65 meters wide, and 0.65 meters high. It's weight in the air is about 86 kg. This vehicle is actuated with two horizontal thrusters for surge and yaw motion, and a vertical thruster for heave motion. Roll and pitch dynamics are not controlled but are intrinsically stable. A 120 meters cable provides electric power to the thrusters and enables communication between the vehicle sensors and the surface equipment. The vehicle is controlled from the surface either manually using joysticks, or automatically by a surface computer. The Phantom 500 is equipped with a 3 axis compass, a depth (pressure) sensor, an altimeter, incremental encoders for the thrusters, a sonar profiler and a video camera.

Figure 1: The Phantom 500.

III THRUSTERS MOTION

A. Model

As most thruster systems, the Phantom propellers are actuated by DC motors. These

[1] Phatom is an underwater robot produced by Deep Ocean Engineering, Palo Alto, USA, used in the projects Narval through a special education/research arrangement.

motors are driven by a power amplifier generating a Pulse Width Modulated (PWM) armature voltage. Neglecting the effect of the screw torque, the dynamics of the thrusters reduces to the dynamics of the DC motors (see for instance [2]). When the mechanical dynamics and the electrical dynamics have different time scales, the motor dynamics can be written as :

$$\dot{\Omega}_t = -a\,\Omega_t + b\,\Delta_t + g$$

where Ωdenotes the rotor speed, Δis the armature voltage duty cycle and γ represents a constant perturbation (acceleration). In symbolic notation, we write the output of this model, the rotation speed as a function of the input signal, Δ and of the initial rotation speed Ω_{t_0} as:

$$\Omega_t = L_{a,b,g}(\Omega_{t_0}, \Delta^t),$$

where $\Delta^t \equiv \{\Delta_u, t_0 \le u \le t\}$ and the operator $L_{a,b,g}(\cdot)$ depends on the parameters of the differential equation.

B Identification

The parameters α and β of the previous equation determine the parametric model of the thrusters dynamics. For a fixed sampling period T,

$$\dot{\Omega}(k) = -a\;\Omega(k) + b\;\Delta(k) + g\;,$$

where we introduced the notation

$$\Omega(k) \equiv \Omega_{kT}\,.$$

Define

$$Y = \begin{bmatrix} \vdots \\ \dot{\Omega}(k) \\ \vdots \end{bmatrix}, q = \begin{bmatrix} a \\ b \\ g \end{bmatrix}, H = \begin{bmatrix} \vdots & \vdots & \vdots \\ -\Omega(k) & \Delta(k) & 1 \\ \vdots & \vdots & \vdots \end{bmatrix}$$

where Y will be designated by *observation vector*, q is the *parameter vector* to be estimated and H is the *observation matrix*.. Using these definitions, the following equation holds

$$Y = Hq.$$

If we consider that we have access to a noisy version of the observation vector, $\hat{Y}$, the previous equation yields

$$\hat{Y} = Hq + e\;.$$

For this model, the estimate that minimizes the quadratic error $J = e^T e$ is given by

$$\hat{q}_{LS} = \left(H^T H\right)^{-1} H^T\,.$$

Note that the quadratic criteria J does not evaluate the difference between the real system output , i.e., rotation speed Ω and the model output, but it rather tries to fit a model to the instantaneous acceleration $\dot{\Omega}$. Moreover, since matrix H is unknown (being estimated from noise corrupted measures), the mean square solution is an approximated solution to the statistical estimation problem.

The observation vector $\hat{Y}$ is not directly measured. Instead, it is estimated using the forward Euler approximation

$$\hat{Y} \approx \frac{1}{T}\begin{bmatrix} \vdots \\ \Omega(k+1) - \Omega(k) \\ \vdots \end{bmatrix}.$$

Consider that the system output measures, $\tilde{\Omega}_t$, are corrupted by additive white Gaussian noise e :

$$\tilde{\Omega}_t = L_q(\Omega_{t_0}, \Delta^t) + e_t\,.$$

The maximum likelihood estimate of the vector q for this problem minimizes the output error criteria

$$J_{ML}(q) = \int_{t_0} \left(\tilde{\Omega}_t - L_q(\Omega_{t_0}, \Delta^t)\right)^2 dt\,,$$

i.e.,

$$\hat{q}_{ML} = \arg\min_q J_{ML}(q).$$

Since we have discrete time observations, the integral in J_{ML} is replaced by a sum over the observation instants. Note that the maximum likelihood estimator minimizes the output error, unlike the previous least squares approach. Determination of $\hat{q}_{ML}$ implies the resolution of a multivariable nonlinear optimisation problem, being highly sensitive to the existence of local minima. We use standard gradient-based optimisation techniques, initialized at the least-squares estimate $\hat{q}_{LS}$.

Using this approach we obtained the following parameters

$$q_{ML} = \begin{bmatrix} a \\ b \\ g \end{bmatrix} = \begin{bmatrix} 3.2526 \\ 8495.3 \\ -307.95 \end{bmatrix}.$$

The signals recorded during an experiment at sea are represented in dashed lines on Fig. 2, along with the output of the identified model (solid line). As this plot shows, the identified model trajectory fits reasonably well the observed response.

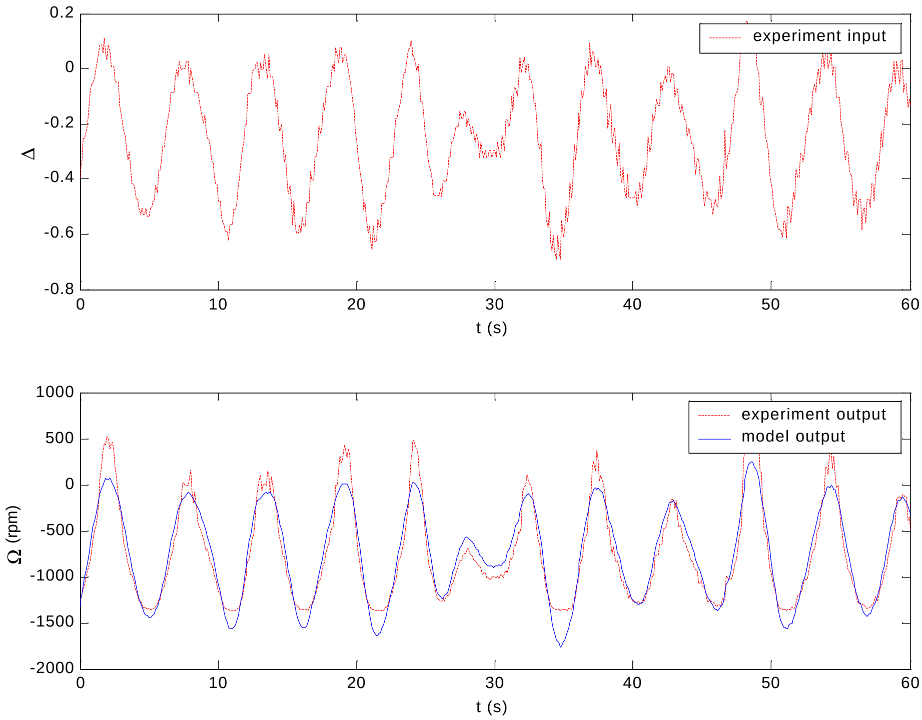

Figure 2 : input duty cycle (up) and measured and modelled output (bottom).

C Controller Design

The objective of this section is to design the discrete time controller which ensures the following close loop properties . For a reference step of 1000 rpm,

(i) the settling time (5 %) is about 0.8 second and the overshoot is acceptable (on the order of 10%).
(ii) the steady state error is zero.
(iii) controller effort (peak control input) is limited in magnitude to the unity.

The controller generates the control signal Δ(n), as a function of the reference signal Ω_r(n), and of the measured output Ω(n). In the z-plane,

$$\Delta(z)=K(z)\left(\Omega_r(z)-\Omega(z)\right),$$

where $K(z)$ is the transfer function of the controller. The system in closed loop with the plant is illustrated on the following figure.

In this figure, $G(z)$ models the discrete time dynamics of the sample data system $G_c(s)$ in series with a zero order hold. Using the model identified in the preceding section,

$$G_c(s)=\frac{b}{p+a}=\frac{8495.3}{p+3.2526}.$$

The discrete time transfer function of the sampled system is given by

$$G(z)=(1-z^{-1})Z\left\{\frac{G_c(s)}{s}\right\}=\frac{725.2848}{z-0.7223}.$$

The controller parameters are computed via the classical root locus design method. This methods achieves acceptable transient control objectives by fixing the root location of the closed loop poles. Control objective (i) is ensured when the controller imposes closed loop poles that satisfy the following two constraints:

$$p_{1,2}=e^{\frac{-3T}{t_R}}e^{\pm jwT}, \quad p_{1,2}=e^{\tan y \quad wT}e^{\pm jwT}$$

where $\tan y=\sin^{-1}x$. For a settling time tr=0.8 s and a damping ratio $x=\sqrt{2}/2$ we obtain $p_{1,2}=0.639\pm0.252\,j$. To satisfy specification (ii), the controller must include an integrator, that is, we choose a Proportional and Integral (PI) controller, transfer function

$$K(z)=k\frac{z-z_k}{z-1}$$

Using the Root Locus method, we compute parameters k and z_k obtaining

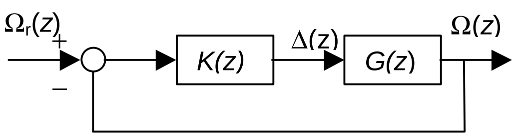

Figure 3: closed-loop system.

$$K(z) = 6.09\times10^{-4}\ \frac{z - 0.563}{z-1}.$$

The next figure shows the root locus of $K(z)G(z)$. Remark that the locus intersects the specified closed loop pole p_1.

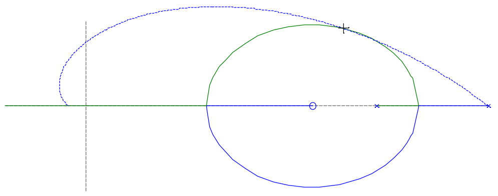

Figure 4: root-locus $K(z)G(z)$.

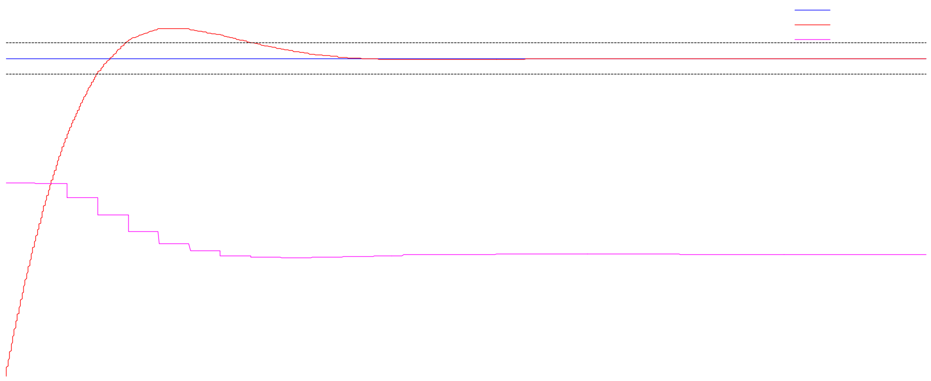

Figure 5 : temporal closed-loop response.

Figure 5 shows the closed loop time response for a step of magnitude of 1000 rpm. The achieved setting time is 0.8 s and the overshoot is about 10%, higher than the expected value of 5%.

V DIVING MOTION

A. Model

To identify a model suitable for control design, we considered a simplified vertical model. More precisely, we consider that all the linear and angular body-referenced velocities are zero except for heave velocity , which is described by a first order non linear model for an acceleration input. In the case of the Phantom 500, the effort delivered by the vertical thrusters depends quadratically on the rotation speed Ω of the DC motor. The simplified model is the following (see [1]) :

$$\dot{w} = -(a + b|w|)\,w + (g + d|\Omega|)\,\Omega.$$

Considering that pitch is close to zero, depth z is approximately related to heave by

$$\dot{z} = w\,.$$

B Identification

The parameters of the of the diving dynamics model are α, β, γ, δ. Yet, to allow controller synthesis using the classical approach of the previous section, we neglect the quadratic damping term. Moreover, we include in the model a constant perturbation h to take into account the positive buoyancy of the vehicle, yielding

$$\dot{w}(k) = -a\,w(k) + (g + d|\Omega(k)|)\Omega(k) + h\,.$$

Define

$$Y = \begin{bmatrix} \vdots \\ \dot{w}(kT) \\ \vdots \end{bmatrix}, \qquad q = \begin{bmatrix} a \\ g \\ d \\ e \end{bmatrix},$$

and

$$H = \begin{bmatrix} \vdots & \vdots & \vdots & \vdots \\ -w(k) & -\Omega(k) & \Omega(k)|\Omega(k)| & 1 \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}.$$

The heave w and its derivative are not directly measured and are estimated using the forward Euler approximation

$$w(k) \approx \frac{1}{T}[z(k+1) - z(k)],$$

and

$$\dot{w}(k) \approx \frac{1}{T^2}[z(k+2) - 2z(k+1) + z(k)],$$ The

solution of this mean square problem gives the initial value for optimisation of the maximum likelihood criterion J_{ML} presented previously, which depends directly on output depth

$$z_t = L_{a,g,d,h}(z_{t_0}, \Omega^t).$$

The input signal and the output signals for an experiment in Villefranche-sur-Mer Bay are plotted in Fig. 6.

The objective of this section is to design the discrete time controller which ensures the following close loop properties. For a reference step of 1 meter,

(i) the settling time (5 %) is about 10 second and the overshoot is acceptable (on the order of 5%).
(ii) the steady state error is zero.
(iii) controller effort (peak control input) is limited in magnitude to 1500 rpm.

Note that the nonlinearity of the identified model comes from the acceleration input

$$a_i = f(\Omega) = (g + d|\Omega|)\Omega.$$

We consider that the vertical dynamics are pre-compensated by a static function such that the reference speed is equal to $\Omega_r = f^{-1}(a_i)$. The plant composed of the static pre-compensator, of the speed controlled thrusters and the vertical dynamics

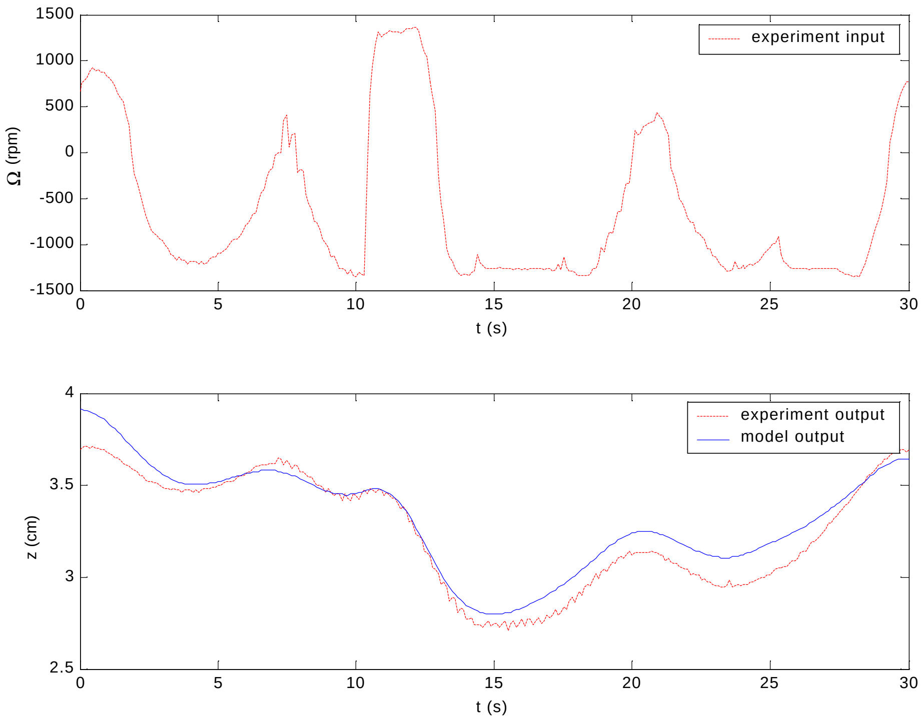

Figure 6: thruster rotation speed (top) and measured and modelled depth (bottom).

becomes

$$\dot{w} = -a\,w + a_i.$$

With this approach, the synthesis problem reduces to the design of a linear controller for the simple linear model of the previous equation. The methid used considers the synthesis of a discrete time controller for the discretized model of the continuous time. The controller transfer function

$$G_c(s) = \frac{1}{p(p+a)} = \frac{1}{p(p+0.581)}$$

The following parameters were identified:

$$q_{ML} = \begin{bmatrix} a \\ g \\ d \\ e \end{bmatrix} = \begin{bmatrix} 0.5813 \\ -3.31\times10^{-5} \\ -7.52\times10^{-8} \\ -0.0813 \end{bmatrix}.$$

C Controller Design

fixes the relation between the speed reference input Ω and depth z.

The discrete time transfer function is computed using the Tustin approximation.

$$G(z) = G_c(s)\Big\|_{s=\frac{2}{T}\frac{z-1}{z+1}} = 2.4\times10^{-3}\frac{(z+1)^2}{(z-1)(z-0.944)}$$

.

A pure integrator is included in the plant, to comply with specification (ii), and we design a lead controller with transfer function

$$K(z) = k\frac{z - z_k}{z - p_k}.$$

Control objective (i) is met if the controller $K(z)$ imposes second order dominant poles at $p_{1,2} = 0.9697 \pm 0.0388j$.

We fix $z_k = 0.944$, making pole-zero compensation. Parameters k and p_k are determined using the root locus method, yielding the following controller:

$$K(z) = 0.3\ \frac{z - 0.944}{z - 0.925}.$$

The root locus of the transfer function $K(z)G(z)$ is plotted in Fig. 7. We can see that the design specifications in the root locus plane are met.

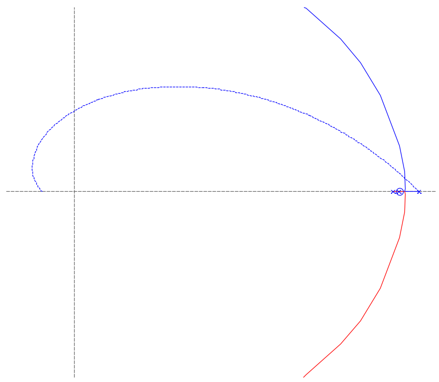

Figure 7: root-locus.

Figure 8 plots the closed loop temporal response to an input step of magnitude 1 meter. The achieved setting time is 10.2 *s* and overshoot is about 9%, higher than the expected value.

VII CONCLUSION AND PERSPECTIVES

In this paper we presented the design of controllers of the body motion of an underwater vehicle. To enable proper design of these controllers, the propellers parameters and the hydro-dynamical model parameters must be identified. A pragmatic approach for the control has been used, decomposing the problem into several decoupled, or slightly coupled problems**.**

The three identical propellers were modelled as first order linear systems. The global dynamic model of the body motion is given by the Euler-Lagrange equations which relate body-referenced linear and angular velocities to the propeller efforts. The simplified heave and heading dynamics were modelled neglecting a subset of the body-reference velocities, leading to first order linear systems with static input nonlinearities. Using an output error criterion (maximum likelihood) initialized by the solution of the common least-squares method, we obtained the values of the physical parameters for the propeller model, the depth model and the heading model.

The propeller speed controller is a linear proportional integral law with parameters obtained using the root-locus synthesis method. For the depth motion, the control is composed of the vertical propeller inner loop and of the depth controller outer loop which includes a nonlinear part (input linearization) and a linear part consisting of a proportional integral with a lead term. The linear part is designed using the root-locus method. The structure and the design of the heading controller have followed a similar approach.

Current hardware problems with the ROV Phantom prevent us to include in this paper results of real experiments of the controlled platform at sea. Comparison of the system response predicted by the identified models and the signals recorded at sea indicate that the identified models predict well the true system behavior, and allow us to expect that the simulation results of the controller performance presented here can be expected to be representative of the behavior that they will yield with the real platform at sea.

The work presented here is a first attempt to design the low-level control system using a model based approach. A major draw-back of the current system is the fact that it relies on simplified decoupled models, valid only under specific operating points (where some velocities and accelerations can be neglected). To be able maintain performance under a wider set of operational regimes, a multi-variable approach is required, to handle coupling between the different degrees of freedom, and explicitly taking into account higher-order terms which are neglected in this paper. On-going studies address this problem by using H_∞ optimisation and/or LMI based control methods.

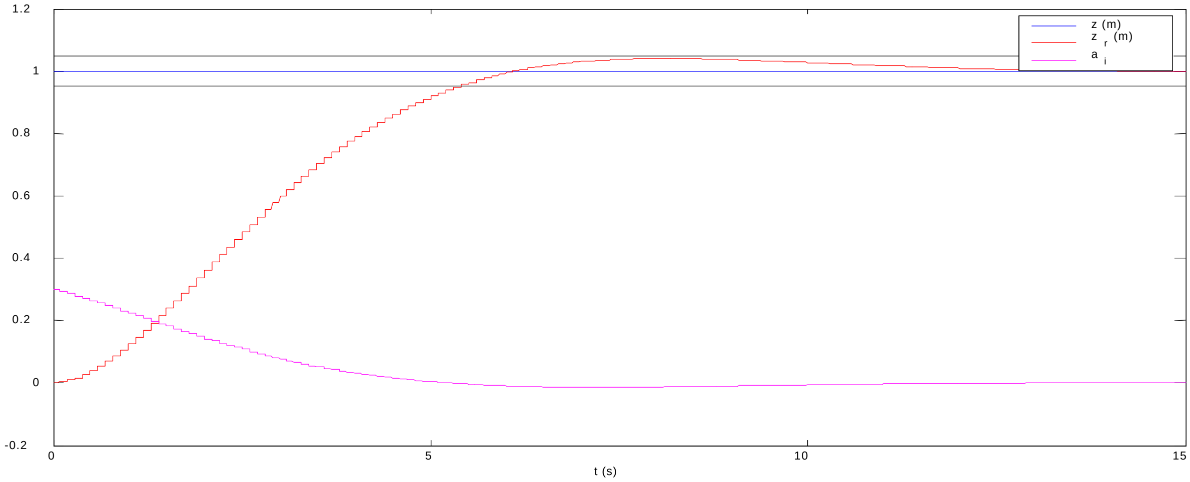

Figure 8: closed-loop response.

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References

[1] T.I. Fossen, *Guidance and control of ocean vehicles*. John Wiley & Sons, 1995.

[2] R. C. Dorf, and R. H. Bishop, *Modern control systems*. Addison-Wesley, 1998.

[3] G. F. Franklin, J. D. Powell and M. L. Workman, *Digital control of dynamic systems*. Addison-Wesley, 1990.

[4] A. Tenas, J. Rendas, and J.-P. Folcher, “Image segmentation by unsupervised adaptive clustering in the distribution space for AUV guidance along sea-bed boundaries using vision’’, To appear in the Proceedings of Oceans’01, Hawaï, 2001.

[5] Bjorn Jalving, “The NDRE-AUV Flight ControlSystem,” *IEEE Journal of Oceanic Eng.*, Vol. 19, No. 4, October 1994.