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Fault detection of actuator faults in unmanned underwater vehicles

A. Alessandri*, M. Caccia, G. Veruggio

Naval Automation Institute, CNR-IAN, National Research Council, Via De Marini 6, 16149 Genova, Italy

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Abstract

A fault-diagnostic system for unmanned underwater vehicles has been designed and tested in real operating conditions. Actuator faults have been considered, relying on approximate models of the vehicles' dynamics. Fault detection and diagnosis is accomplished by evaluating any significant change in the behaviour of the vehicle. This task is performed by a bank of estimators: a filter is implemented for each actuator fault type, including the no-fault case. The estimators used are extended Kalman filters (EKF), due to the presence of nonlinearities in the dynamic models. Experimental results are reported, to demonstrate the effectiveness of the proposed approach. © *1999 Published by Elsevier Science Ltd. All rights reserved.*

Keywords: Fault modelling; Fault diagnosis; Fault detection; Fault isolation; Extended Kalman filter; Underwater vehicles

1. Introduction

The surveying and maintenance of benthic stations and off-shore platforms, scientific and environmental data acquisition, and marine warfare have encouraged the development of unmanned underwater vehicles (UUVs), which are usually classified as either autonomous underwater vehicles (AUVs) or remotely operated vehicles (ROVs). Operational activity requires the vehicles to be able to detect and recover from subsystem, sensor, and actuator faults, in order to continue a mission in some form, even if the human operator cannot intervene to fix the problem. The low communication bandwidth of the acoustic channels and/or malfunctions in the communication devices can reduce the possibilities for human supervision of the UUVs performance. Recent advances in fault diagnostics have now made feasible the development of automated fault diagnosis and accommodation in the area of underwater robotics, to increase their reliability during autonomous missions. In this paper, the possibility of designing a fault-tolerant UUV is explored, based on the experience gained on the Roby 2 ROV (Veruggio et al., 1994), a testbed UUV developed at the Naval Automation Institute (CNR-IAN), National Research Council, Genova, Italy. More specifically, the focus is on the problem of detecting and isolating actuator faults.

Among the various fault-detection approaches a distinction has arisen between the model-free and model-based paradigms (Gertler, 1988; Frank, 1990). Model-free fault diagnosis includes all the techniques that do not rely upon models of the underlying system, while model-based methods try to diagnose faults using the redundancy of some mathematical description of the dynamics. Examples of model-free techniques are the methods based on spectral analysis, pattern recognition and statistical classification, and the classical limit and trend check (Pau, 1981). Model-free techniques are widely employed whenever no model of the plant is available, and the cost of developing a model is too high with respect to the benefits; a typical field of application for this kind of method includes large-scale systems.

From the beginning of the seventies, there have been numerous theoretical advancements in fault diagnostics based on analytical redundancy (Willsky, 1976). According to this approach, all the information on the system can be used to monitor the behaviour of the plant, including the knowledge about the dynamics. The presence of faults is detected by means of the so-called 'residuals', i.e., quantities that are over-sensitive to the malfunctions. Residual generation can be performed in

*Corresponding author. Fax: +39 10 6475600; e-mail: angelo@ian.ge.cnr.it.

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different ways: parity equations (Gertler and Singer, 1990), observer-based generation (Frank, 1990), and the methods based on parameter estimation (Isermann, 1984). The method using parity equations is a direct implementation of the idea of detecting deviations of the system due to faults, by imposing a direction on the residuals as a response to a particular fault. In this way, a high degree of isolation is guaranteed, although it must be relaxed for the specifications about causality and stability.

A less general method corresponds to the so-called 'structured design of the residuals', i.e., only a subset of residuals becomes nonzero in response to a particular fault. Observer-based techniques belong to this category, and can be seen as special cases of parity equations (Chow and Willsky, 1984). The innovation sequence generated by the filter is considered as residuals (Willsky, 1976); in any event, different schemes can be devised to enhance isolability, as pointed out in (Frank, 1990). Another example of model-based techniques includes the methods based on parameter estimation. Parameter-identification-based methods are more practical than other kinds of techniques, because they try to detect faults by estimating significant parameters of the plant. The assumption is that the faults are reflected in the physical characteristics of the system in terms of parameter changes (Isermann, 1984). The mathematical parameters of the plant (some of them may have a physical meaning) can change as a consequence of faults. Parameter estimation is performed on-line, and the estimated parameters are compared with the nominal ones, which correspond to fault-free conditions. In this way, supervision of the system performance is obtained.

In the literature, numerous applications of fault diagnosis are reported for aeronautical and aerospace systems, automotive and traffic systems, chemical processes, electrical and electronic systems, nuclear plants, power systems, and transportation systems (Isermann and Ballé, 1997). Only recently, has attention been devoted to fault diagnostics for marine and underwater systems. As previously discussed, the first choice that must be made is between model-free and model-based techniques. Model-based fault diagnosis seems more suitable for underwater applications. A model of the vehicle is usually available, because the physical laws describing the dynamics of a UUV are well-known and the number of state variables is small (Fossen, 1994). Past research on fault diagnostics for underwater robotics applications have focused mainly on techniques for parameter estimation.

Parameter estimation may be accomplished in different ways. If nothing is known about the plant, a black-box approach is applied: a linear or nonlinear model is tuned by means of the available data (Söderström and Stoica, 1989). With respect to the problem of fault detection for underwater vehicles, an example of this kind of approach is suggested in (Rae and Dunn, 1994). If there exist physical laws that are well-suited to describe the plant, except for some parameters that are yet to be determined, the unknown parameters can be obtained from the measured inputs and outputs by means of an on-line recursive identification, relying on a state-space model (Söderström and Stoica, 1989). Both state and unknown parameter vectors are estimated in the presence of noisy measurements by applying the so-called 'state-augmentation', which consists of an enlargement of the state space. The new state vector is given by the state of the original system, and by the uncertain parameters. Thus, the problem becomes one of estimating the state of the augmented system. According to this view, experience in fault detection for underwater robotics are reported in (Healey, 1992, 1993). An observer-based technique is proposed in (Alekseev et al., 1994): reduced-order observers are used to detect sensor and thruster faults. Moreover, the importance and the difficulties of developing a model for a tethered UUV are discussed.

Fault diagnosis and accommodation involve all the levels of the control architecture of a UUV: residual generation is a synchronous task to be carried out at the lowest level, but the detection process determines events towards the upper levels. Accommodation involves the reconfiguration of the vehicle or of the mission, and thus is related to both the intermediate and the top levels of the control architecture. The problem of the integration of fault-tolerant capabilities within the frameworks of the various control architectures for UUVs is still open. A comprehensive discussion of this topic for general fault-tolerant systems is reported in (Blanke et al., 1997).

In this paper, the diagnosis of actuator faults in the UUV Roby 2 is investigated and the design of a fault detection system is considered, using a model-based approach. The dynamic models developed for Roby 2 are illustrated in Section 2. In Section 3, fault models are considered, to describe the dynamics of the vehicle with actuator faults. A fault-detection scheme, based on a bank of EKFs, is proposed in Section 4. The EKFs used for residual generation rely on the models described in Sections 2 and 3. The results of the experimental tests on Roby 2 are reported and discussed in Sections 5 and 6. Section 5 focuses on the residual generation and filtering. Section 6 deals with the problem of taking a decision about the faults, by means of all the available information. Finally, Section 7 is devoted to the conclusions and to the prospects for future work.

2. Dynamic models for unmanned underwater vehicles

In this work, a problem of fault detection for a vehicle operating on the horizontal plane is considered. The underwater vehicle is Roby 2, a tethered UUV, which has been deployed in various missions both in the Mediterranean and in Antarctica (Bono et al., 1994). Roby 2 is

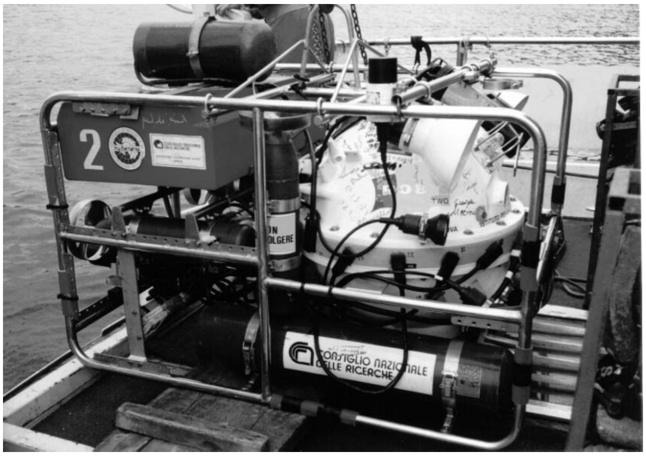

Fig. 1. Roby 2.

neutrally buoyant in water, structurally stable in pitch and roll, and is provided with four DC motors. Fig. 1 shows Roby 2 in the operational configuration for sea tests.

A small UUV can be modelled by a set of hydrodynamic equations (Fossen, 1994). In particular, the horizontal motion can be described by the following nonlinear equations:

$$m_u \dot{u} = m_v v r - k_u u - k_{u|u|}\, u|u| + F_u, \tag{1}$$

$$m_v \dot{v} = -\, m_u u r - k_v v - k_{v|v|}\, v|v| + F_v, \tag{2}$$

$$I_z \ddot{\psi} = -\,(m_v - m_u)\, u v - k_{\dot{\psi}|\dot{\psi}|}\, \dot{\psi}|\dot{\psi}| + M_z, \tag{3}$$

where m_u, m_v, and I_z are the masses along the longitudinal and transverse axes and the inertia around the vertical axis of the vehicle, respectively (all including the hydrodynamic added inertial terms); u and v are the vehicle surge and sway speeds of the vehicle-fixed reference frame with respect to the universal reference frame, and ψ is the vehicle heading; F_u, F_v, and M_z are the surge force, the sway force, and the yaw torque due to the actuators. The parameters k_u and $k_{u|u|}$ are the linear and quadratic drag coefficients for the surge motion, while k_v and $k_{v|v|}$ are those for the sway motion; finally, $k_{\dot{\psi}}$ and $k_{\dot{\psi}|\dot{\psi}|}$ describe the effects of the drag in the yaw dynamics.

Since Roby 2 is equipped with two horizontal thrusters, the vehicle is not fully controllable in the horizontal plane (see Fig. 2 for a pictorial representation). The two vertical thrusters enable it to keep a constant depth, so that the motion of the vehicle remains on the plane. If the sway force F_v is assumed to be zero, since no transverse thruster is mounted on the vehicle (i.e., there is no thrust in the sway direction, see Fig. 2), the dynamic equations can be approximated by the following two decoupled equations:

$$m_u \dot{u} = -\, k_u u - k_{u|u}u|u| + F_u, \tag{4}$$

$$I_z \ddot{\psi} = -\, k_{\dot{\psi}}\, \dot{\psi} - k_{\dot{\psi}|\dot{\psi}|}\, \dot{\psi}|\dot{\psi}| + M_z. \tag{5}$$

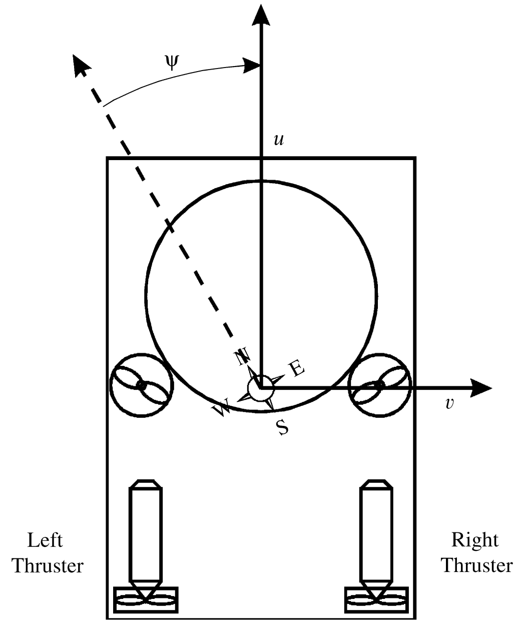

Fig. 2. Picture of a UUV operating on a horizontal plane.

In particular (denoting by T_{HL} and T_{HR} the thrusts exerted by the left and right horizontal propellers, respectively, and by $d = 0.3$ m the arm of these applied forces with respect to the axis of the vehicle), F_u and M_z are

$$\begin{aligned} F_u &= T_{HL} + T_{HR}, \\ M_z &= (T_{HL} - T_{HR})\, d. \end{aligned} \tag{6}$$

Each propeller thrust can be expressed by (Fossen, 1994):

$$T\,(n, v_a) = \alpha\, n|n| - \beta|n| v_a, \tag{7}$$

where n is the propeller revolution rate, α and β are real positive constants, and v_a the advance speed of the propeller (Fossen, 1994). The input/output relationships of the propellers have been identified at bollard conditions (i.e., $v_a = 0$) in thrust tunnel tests. This approximation is reasonable because Roby 2's operational speed is very low (less than 30 cm/s when high motion precision is required). Moreover, the propeller revolution is proportional to the propulsor applied voltage: the voltage-to-thrust coefficients have been identified by tests carried out in a thrust tunnel (Bruzzone and Spirandelli, 1995) and the relationships are $T_{HL} = 0.4501\, V_{HL}|V_{HL}|$ and $T_{HR} = 0.5573\, V_{HR}\,|V_{HR}|$, where V_{HL} and V_{HR} are the voltages applied to the left and right motors, respectively.

Two separate identification procedures were applied for the estimation of the coefficients of Eqs. (4) and (5), respectively. The results are as follows: $k_u = 20.4$ N/(m/s), $k_{u|u|} = 272.9$ N/(m/s)^2, $m_u = 454.5$ kg for Eq. (4); $k_{\dot{\psi}} = 11.4$ N m/(rad/s), $k_{\dot{\psi}|\dot{\psi}|} = 66.3$ Nm/(rad/s)^2, $I_z = 66.7$ kg m^2 for Eq. (5). Further details about this topic are reported in Alessandri et al. (1997a, c).

3. Actuator fault modelling

In order to describe the fault models of the vehicle, it is necessary to give a brief account of the design of the control system. Apart from the guidance (which involves issues beyond the scope of this paper), the control is based on an open-loop selection of the surge thrust, and on a closed-loop steering controller. On the basis of the model described by Eq. (5), a simple PID controller has been designed to perform autoheading. Clearly, an interplay is established between the thrust required for steering and the thrust chosen for the surge motion (Alessandri et al., 1997b).

Denote by F_u^* the desired surge thrust, M_z^* the desired torque along the z-axis, and ψ^* the set point of the yaw angle; T_{HL}^* and T_{HR}^* are the desired thrust exerted by the propellers

$$T_{HL}^* = \frac{1}{2}\left(F_u^* + \frac{M_z^*}{d}\right),$$
$$T_{HR}^* = \frac{1}{2}\left(F_u^* - \frac{M_z^*}{d}\right). \tag{8}$$

When no fault occurs

$$T_{HL} = T_{HL}^*,$$
$$T_{RL} = T_{RL}^*, \tag{9}$$

and then

$$F_u = F_u^*,$$
$$M_z = M_z^*. \tag{10}$$

In this way, the PID regulator computes the desired torque M_z^*. In Fig. 3 all the components of the control loop are depicted. More specifically, there is an anti-windup PID regulator with gains equal to 300.0, 2000.0, and 0.1, for the proportional, derivative, and integral actions, respectively. The closed-loop system requires the introduction of a Kalman filter to reduce the noise in the measurements of the yaw. The Kalman filter has been designed on the basis of a simple kinematic model. The PID regulator generates the desired torque M_z^*.

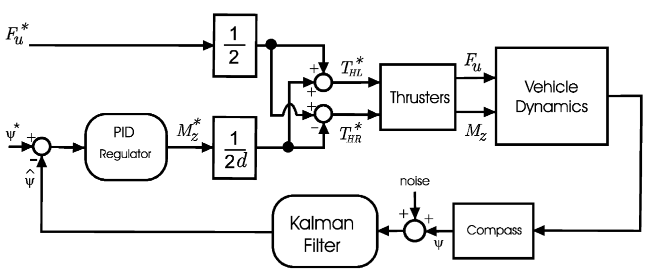

Fig. 3. Roby 2's control loop.

If a total breakdown of the horizontal left thruster occurs, $T_{HL} = 0$, and then the resulting surge force and yaw torque are

$$F_u = \frac{1}{2}\left(F_u^* - \frac{M_z^*}{d}\right),$$
$$M_z = \tfrac{1}{2}(M_z^* - F_u^* d). \tag{11}$$

Similarly, when the horizontal right thruster breaks down, the equations become

$$F_u = \frac{1}{2}\left(F_u^* + \frac{M_z^*}{d}\right),$$
$$M_z = \tfrac{1}{2}(M_z^* + F_u^* d). \tag{12}$$

Eqs. (11) and (12) shows that the fault acts on the dynamics of the vehicle as a virtual disturbance, for which the controller tries to compensate. At steady state after the occurrence of the fault, the desired yaw torque equals the opposite of the disturbance. On the basis of this model, a horizontal thruster fault causes a drop in the speed, but no change in the tracked orientation.

4. A fault-detection scheme for underwater vehicles

In a general fault-detection framework, there exist three types of models: a model of the normal process, a model of the observed process, a set of fault models (Isermann, 1984). All the fault-detection methods are based on the idea of determining a change in the normal behaviour of the system by comparing the state, the parameters, and other related quantities of the observed process with those of the normal and faulty processes. An assessment of the change in these variables is given by the so-called 'residuals', which are indices of model matching. Ideally, the residuals are zero in the case of perfect matching without noise; otherwise, the residuals can be evaluated in different ways, and this is the subject of Section 6. A decision scheme based on the results of these evaluations may be quite complex, depending on the dimension of the plant and on the desired performance, robustness, and real-time operating capabilities (Frank, 1990). Using the different methods, fault diagnostics can be attained by a bank of estimators. Each estimator is able to generate an estimate of the state and of the relevant parameters for a particular fault hypothesis. The residuals corresponding to a fault hypothesis measure the discrepancies between the predicted behaviour of the system and what stems from the available measurements. This scheme guarantees effective isolation, at the cost of greater computational burden. Typical fields of application of observer-based residual generation are aircraft applications (Eide and Maybeck, 1996).

On the basis of the healthy and fault models described in Section 2, a bank of estimators has been considered for

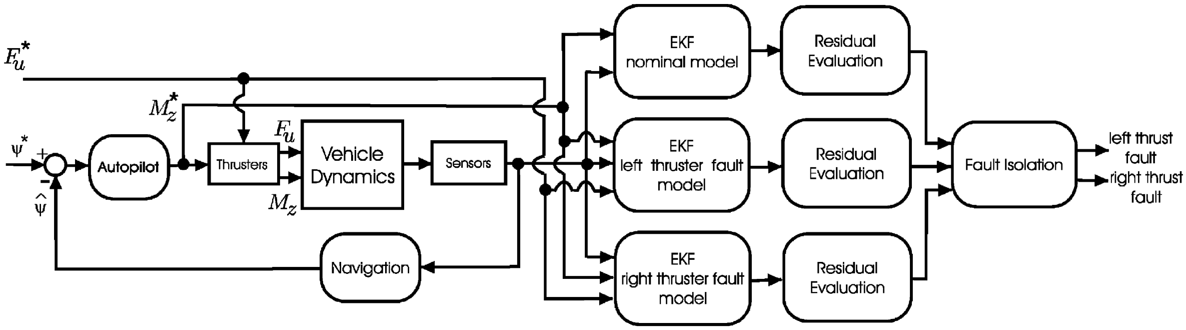

Fig. 4. An observer-based fault-diagnostic scheme.

the nominal plant, the left actuator fault, and the right actuator fault. These estimators rely on the state Eq. (5), which is nonlinear due to the presence of quadratic terms. The first EKF monitors the behaviour of the vehicle when there is no fault, and uses Eq. (10). The second EKF enables one to generate residuals when a fault of the left actuator occurs and uses Eq. (11). Finally, the last one is devoted to the residuals for the fault of the right propeller, and relies on Eq. (12). In Fig. 4, a sketch of the fault-detection and isolation scheme is shown. The next few paragraphs will consider the problem of residual generation and evaluation.

5. Residual generation and filtering

The fault-detection scheme proposed here has been tested on experimental data collected during pool tests with Roby 2: artificial single failures of the propulsors were caused by acting on the horizontal thrusters while the autopilot is operating as described in Section 3. The only available sensor was a KVH DGC 100 compass. Obviously, a more efficient design of the fault-diagnostic system would require the integration of other instrumentation, such as rate gyros, Doppler velocimeter, sonar, short and long baseline positioning systems, and echo-sounder.

The residuals are the difference between the measured and the estimated value of the same variable at each time instant (the sample time is 0.1 s). In order to improve the isolation capabilities, the residuals are filtered with low-pass filters against the effects of noise. Low-pass filtering enables one to extract the steady-state value and to reduce the variance of the residual. As a consequence, the threshold can be chosen less conservatively, and the performance of the diagnostics system is improved.

Low-pass filters can be applied for residual filtering, with particular care in the case of directional residuals because of the geometric properties. In this case, the filters must be identical for each type of filter. If the residuals are structured (as here), the filters can be designed independently from one another (Gertler et al., 1995). Many low-pass filtering techniques are available in the literature. Simple second-order Butterworth filters with cut-off frequencies at 0.2 Hz have been used here to process all the residuals.

The tests presented in this section refer to cases where the vehicle is advancing ahead at a constant speed of almost 0.2 m/s. In the case of Figs. 5–8, after almost 15 s, a right thruster fault is forced by switching off the right propeller. The fault causes a change in the behaviour of the vehicle, due to the prevalence of the left thrust. The fault induces a disturbance, which is compensated for by the steering controller, as shown in Fig. 5. As one can notice in Fig. 6, the residuals of the EKF based on the model of the nominal plant increase after the occurrence of the fault, as well as those of the estimator with the model of the left propeller fault (see Fig. 7). Indeed, the residuals of the EKF based on the model of the right propeller fault become smaller, as depicted in Fig. 8.

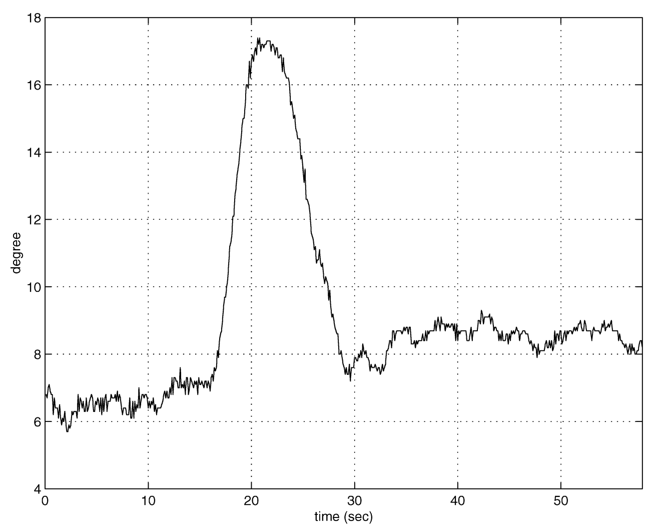

Fig. 5. Measurements of the yaw (right fault).

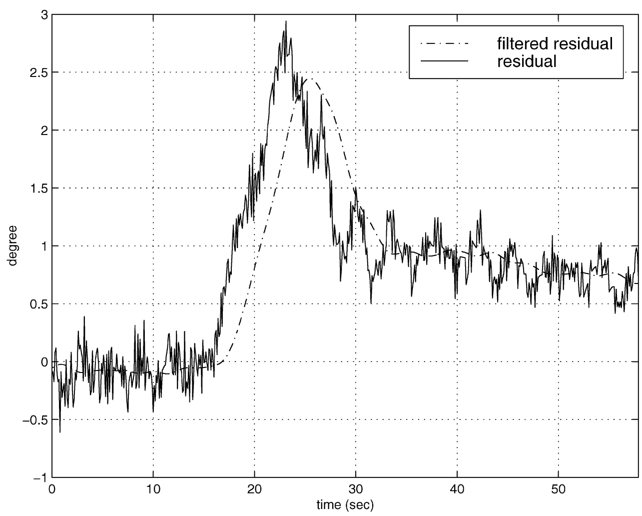

Fig. 6. Nominal plant model residual (right fault).

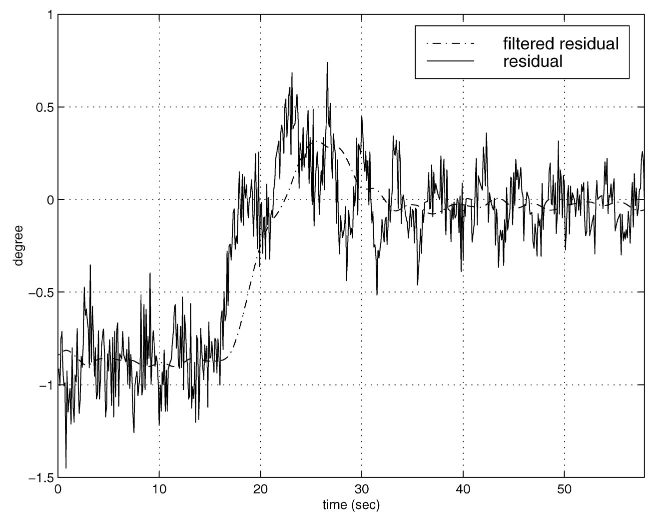

Fig. 8. Right fault model residual (right fault).

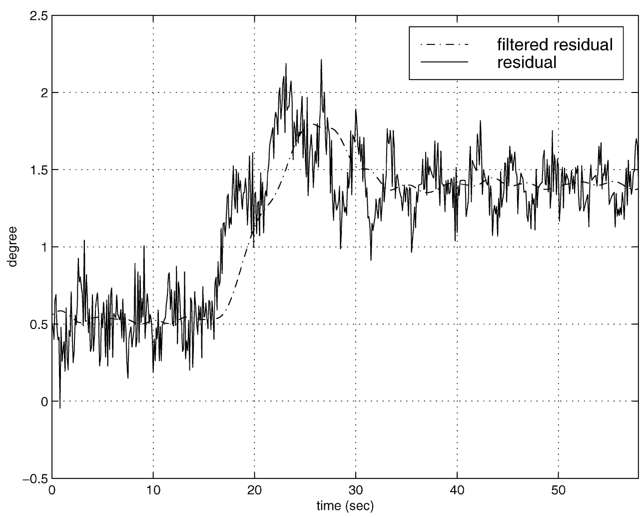

Fig. 7. Left fault model residual (right fault).

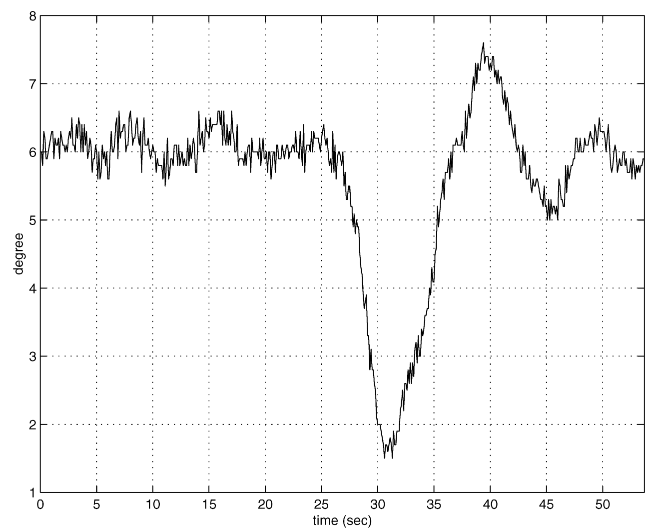

Fig. 9. Measurements of the yaw (left fault).

In the next section the residuals are used to decide about the faults.

The effects of a partial left fault at $t = 25$ s are depicted in Figs. 9–12. As in the previous case, the fault is compensated for by the controller; however, the residual generators perform worse since there is no exact matching between the models of the observers and the real malfunction.

6. Residual evaluation and decision

The fault detection and isolation scheme is completed by a module that is responsible for residual evaluation and for making decisions. On the basis of the residual generation, the decision scheme could be designed in various different ways (Basseville, 1988; Leonhardt and Ayoubi, 1997). The basic steps are: (i) to collect the residuals, (ii) to compute the required quantities as functions of the residuals, and (iii) choose the thresholds for each filter. These points will be addressed below.

Consider the fault detection scheme presented in Section 4: basically there exist three kinds of residual, corresponding to the no-fault case, a left fault, and a right fault. A classification can be made on a single fault by a simple threshold comparison. More specifically, an indication equal to 1 is given if the absolute value of the residual is under the threshold (these indications are denoted by `nom_res_low`, `left_fault_res_low`, and `right_fault_res_low`); otherwise the indication is

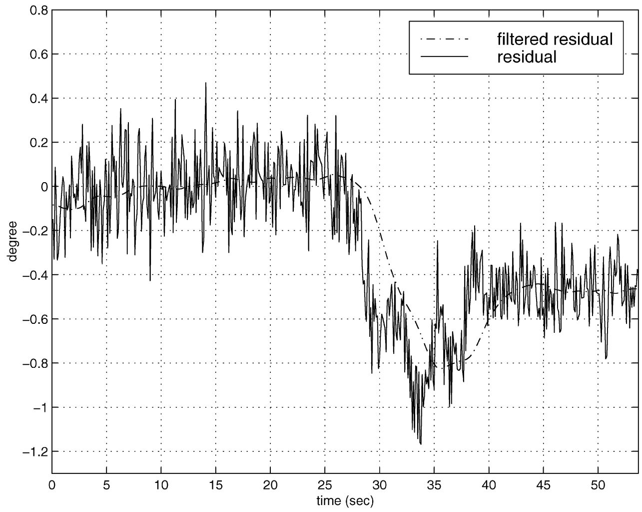

Fig. 10. Nominal plant model residual (left model).

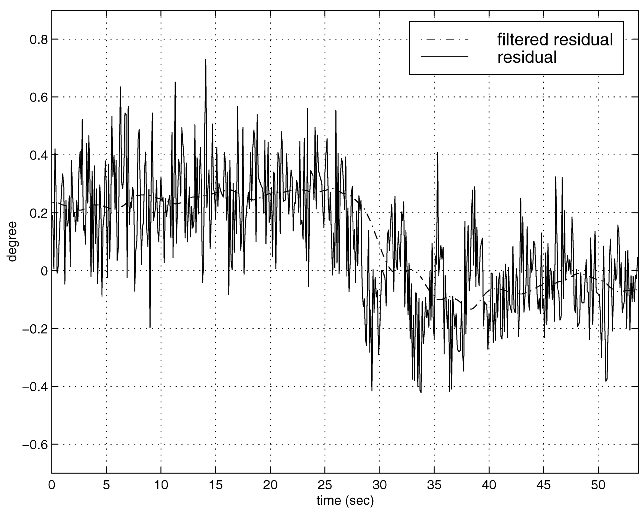

Fig. 11. Left fault model residual (left fault).

equal to 0. If NOT denotes the Boolean negation and AND the 'and' boolean operation, simple diagnostic rules can be expressed as follows:

left_fault = NOT(nom_res_low) AND left_fault_res_low AND NOT(right_fault_res_low) (13)

right_fault = NOT(nom_res_low) AND NOT(left_fault_res_low) AND right_fault_res_low (14)

The results obtained with a threshold equal to 0.458°, with the compass residuals presented in Section 5, are depicted in Figs. 13 and 14 (right actuator fault) and Figs. 15 and 16 (left actuator fault). As expected in the

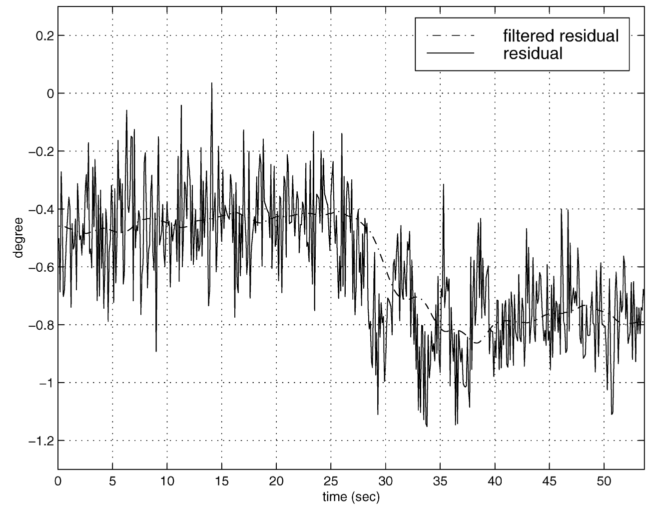

Fig. 12. Right fault model residual (left fault).

case of Figs. 15 and 16, the proposed decision method performs worse.

In order to assess the evaluation capabilities of the proposed decision rule, a test without faults is considered, as shown in Fig. 17 (surge force), Fig. 18 (estimated speed), and Fig. 19 (measurements of the yaw). The vehicle is moving along a straight line, and the reference set-point is at almost 22° (see Fig. 19). The value of the surge force is changed manually according to the profile depicted in Fig. 17. The advance speed of Fig. 18 has been estimated using an EKF and Eq. (4) with sonar measurements (Alessandri et al., 1997a). The compass residuals are shown in Figs. 20–22. Note that the manoeuvres cause variations of the residuals because of the coupled dynamics of Eqs. (1)–(3).

The application of the diagnostic rules (13) and (14) gives the results summarized in Figs. 23 and 24.

As can be noticed in Figs. 13, 14, 15, 16, and 23, 24, the residual filtering improves the performance of the fault-diagnosis system, since the unprocessed residuals applied to the same decision rules determine higher false alarm and misdetection rates.

The evaluation of the residuals can be improved by integrating all the available information, such as, in the case of an underwater system, the external conditions of the environment or information related to the dynamics but not included in the model of the residual generator. This important subject has been addressed only recently (see, for instance, Zhuang and Frank (1997) and Thilliol et al. (1997)). For instance, the revolution rate and the current absorption of the propulsors are useful in monitoring the performance of the vehicle in cases of thruster malfunctions. If a leakage occurs in the canister containing one of the DC motors, an abnormal increase in the current is measured.

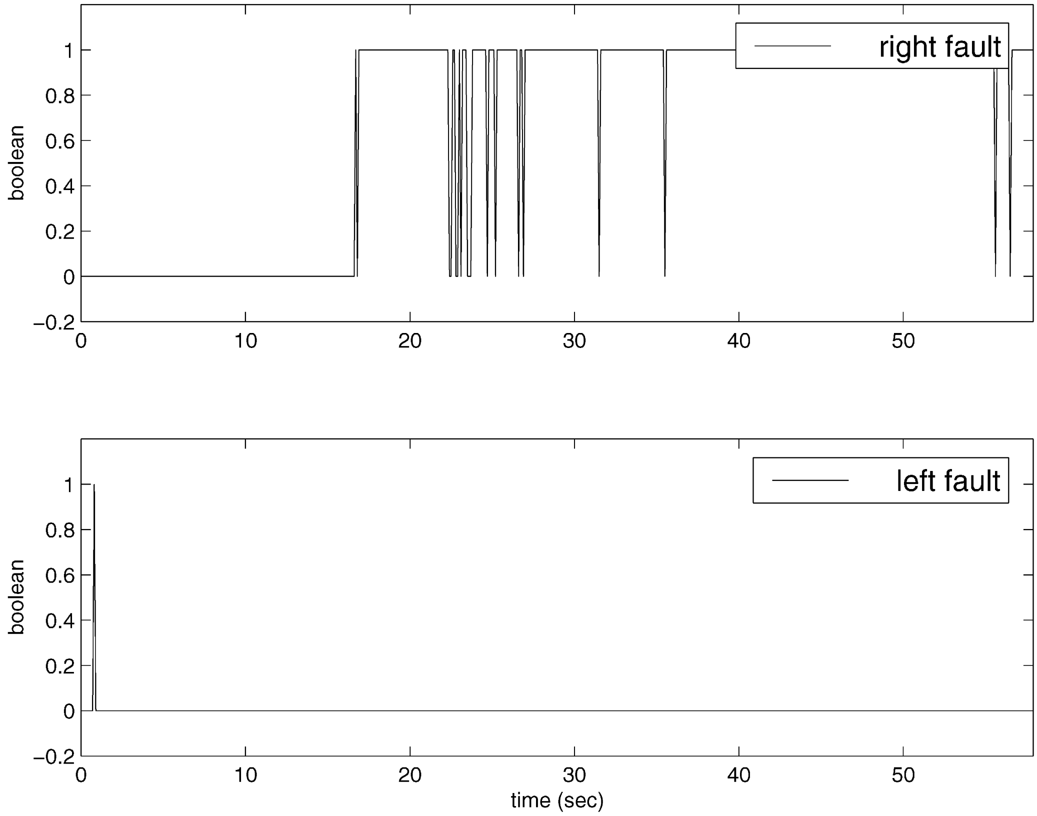

Fig. 13. Unprocessed residuals decision (right fault).

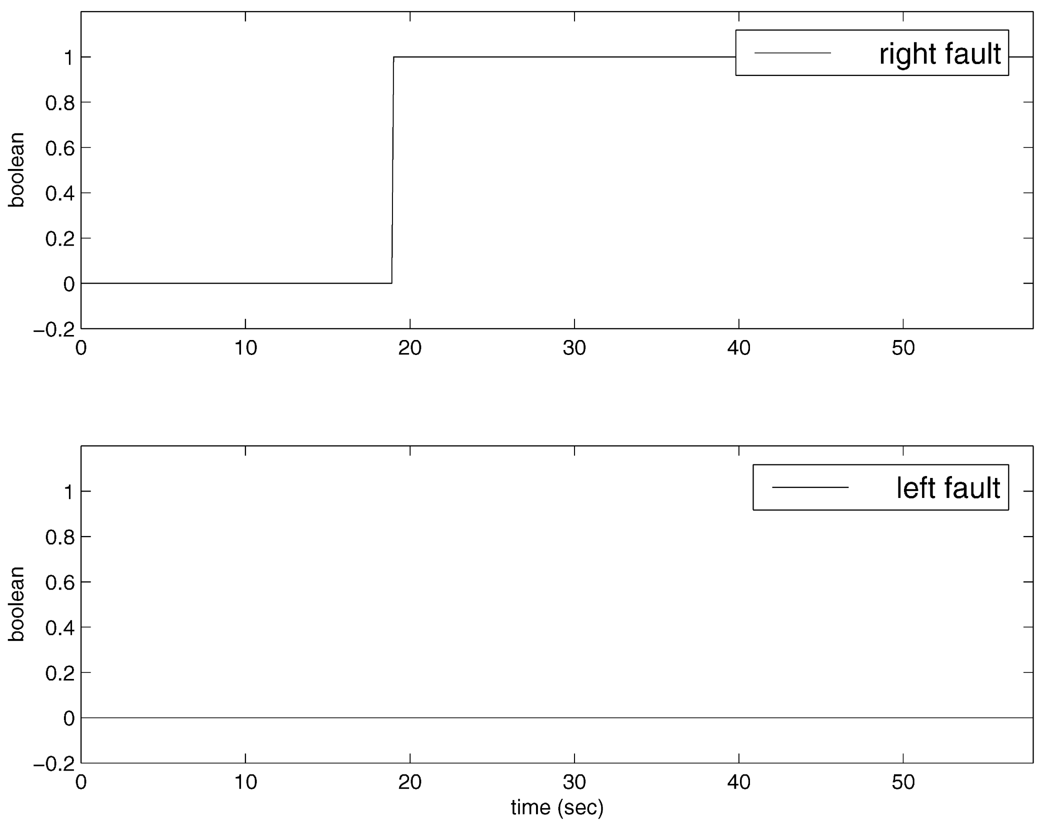

Fig. 14. Filtered residuals decision (right fault).

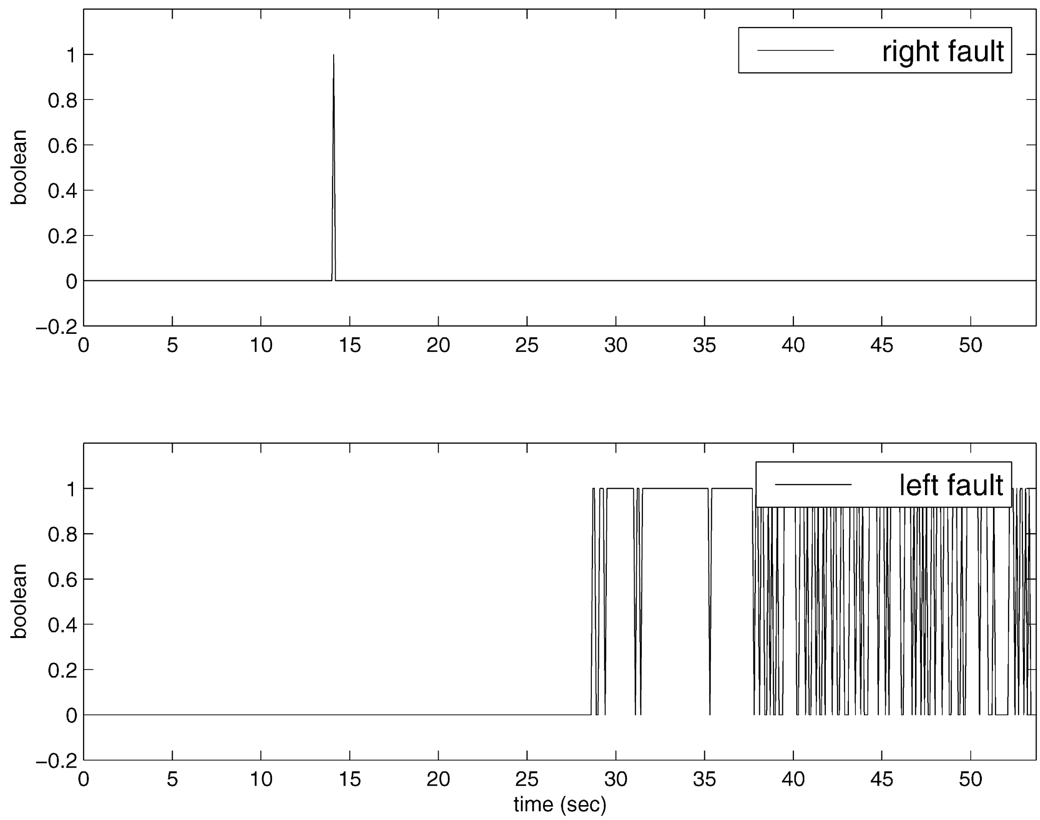

Fig. 15. Unprocessed residuals decision (left fault).

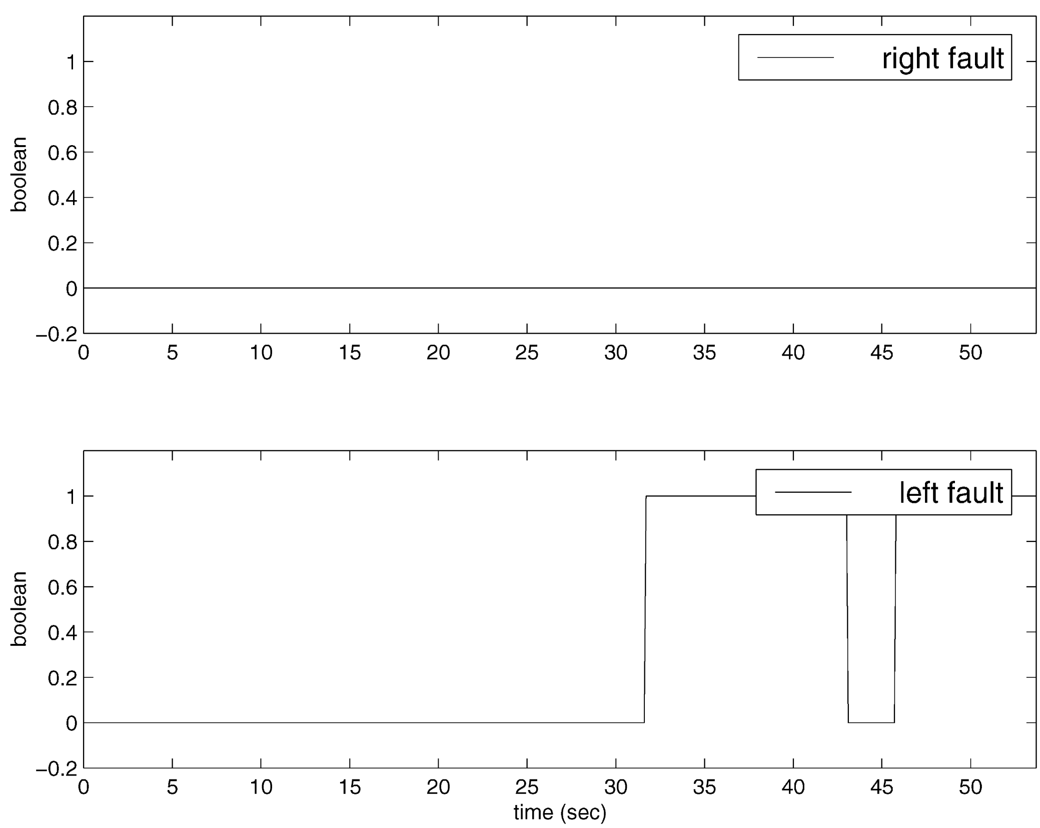

Fig. 16. Filtered residuals decision (left fault).

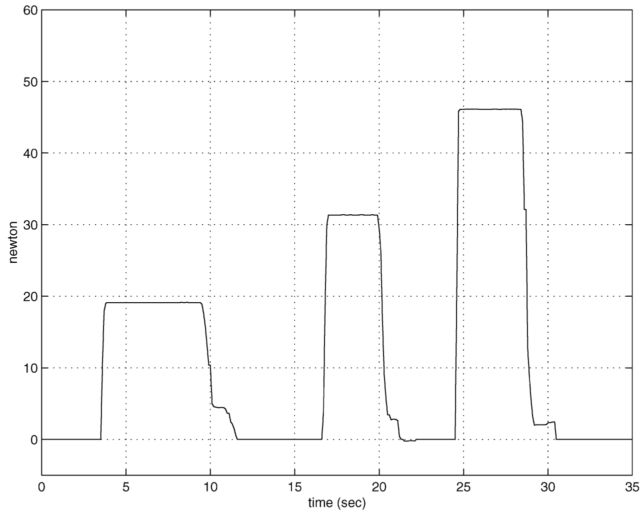

Fig. 17. Surge force (no fault).

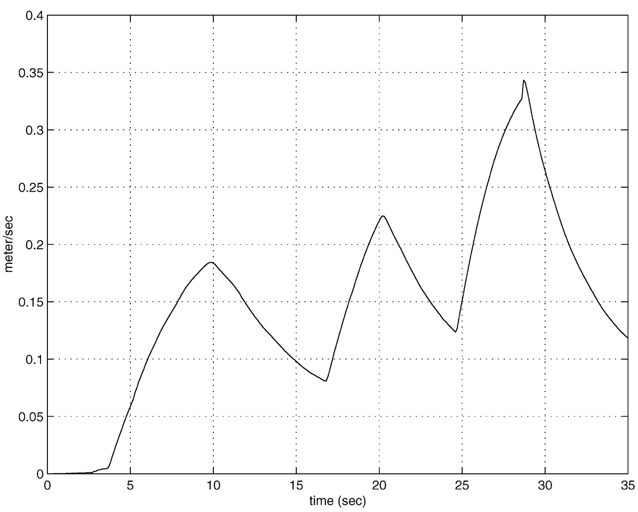

Fig. 18. Estimate of the surge speed (no fault).

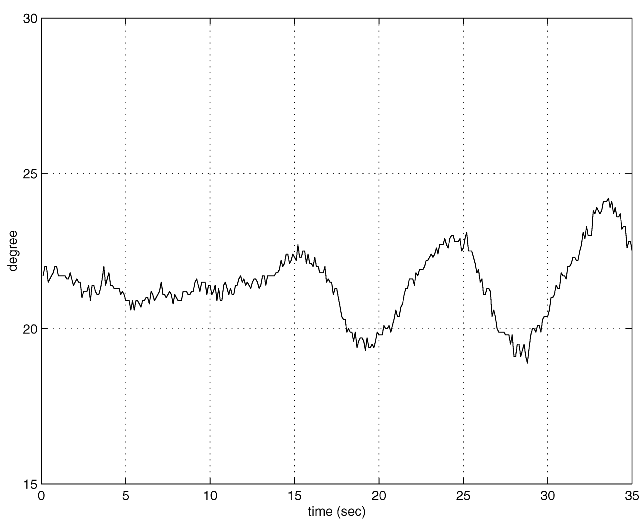

Fig. 19. Measurements of the yaw (no fault).

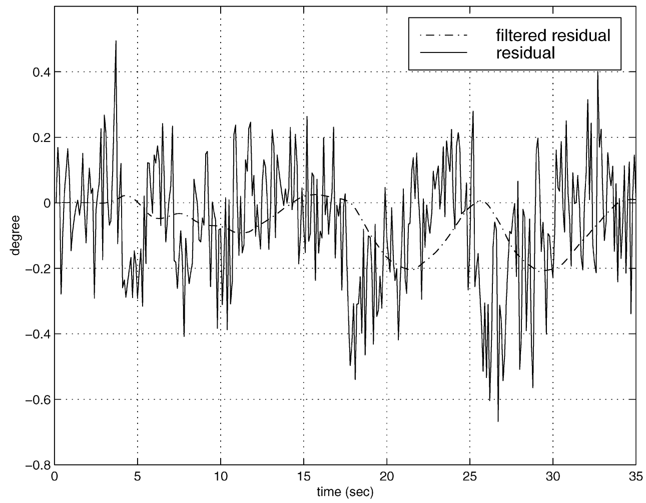

Fig. 20. Nominal plant model residual (no fault).

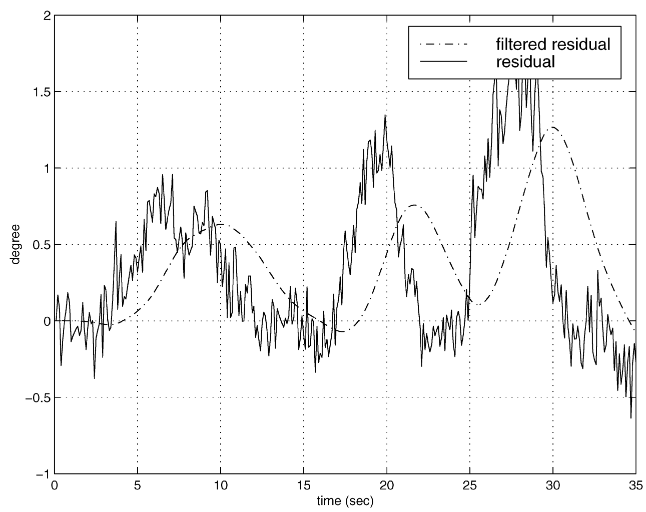

Fig. 21. Left fault model residual (no fault).

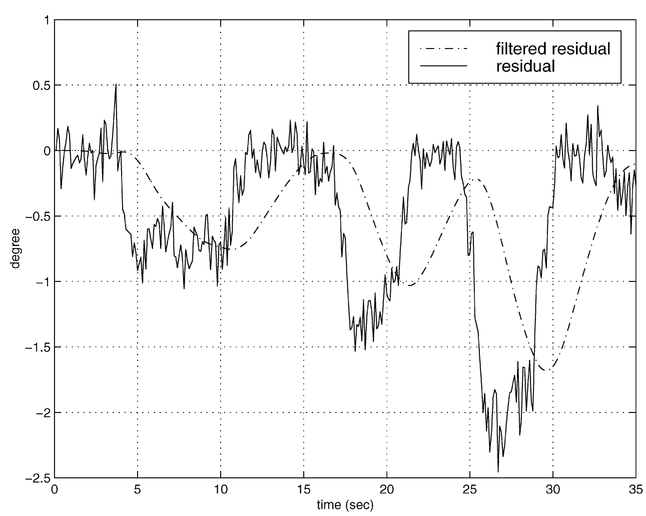

Fig. 22. Right fault model residual (no fault).

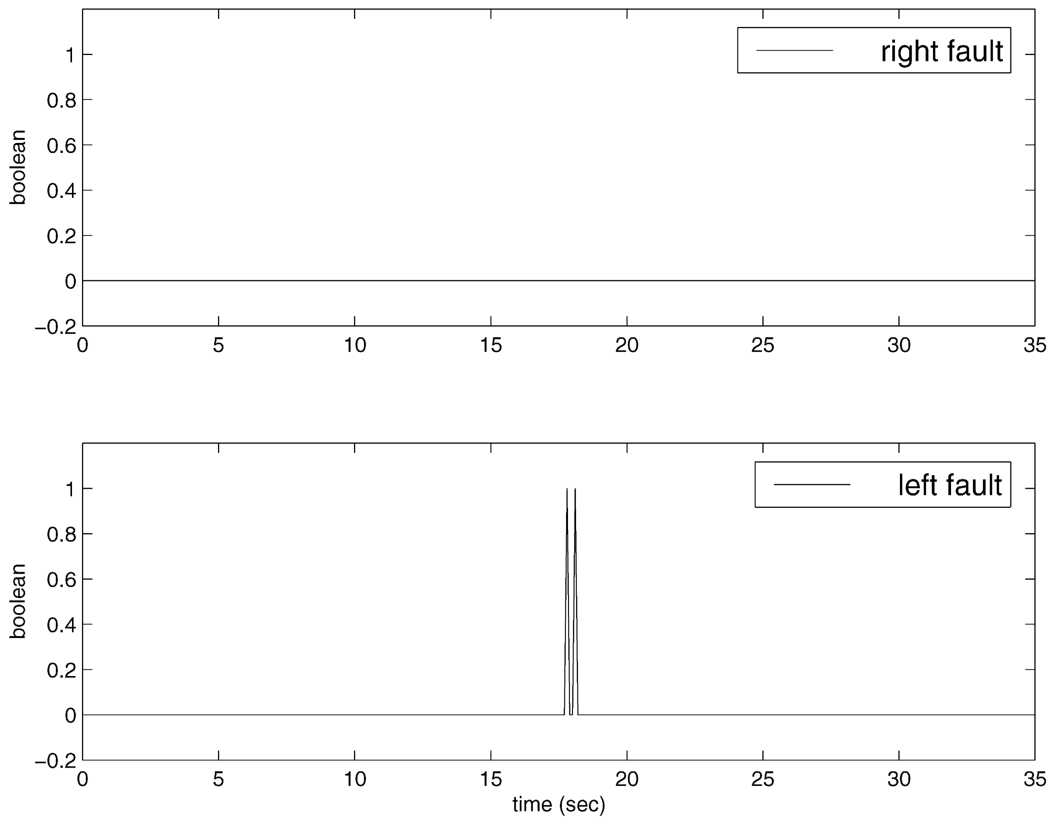

Fig. 23. Unprocessed residuals decision (no fault).

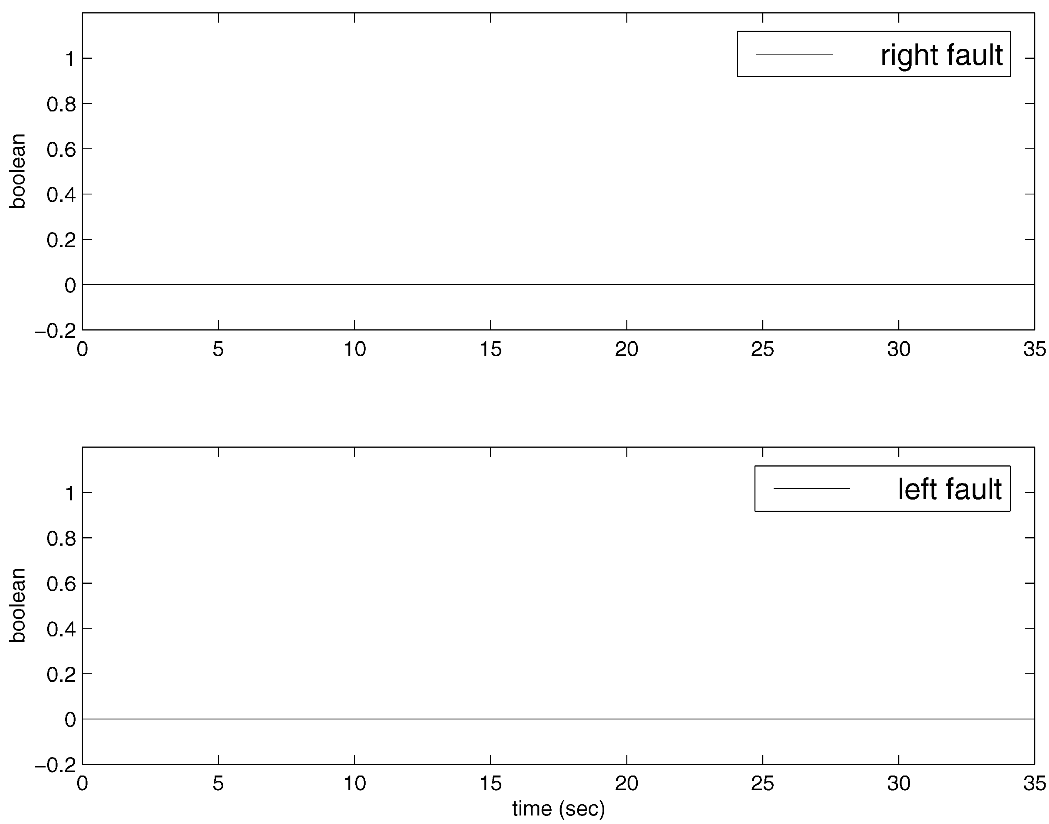

Fig. 24. Filtered residuals decision (no fault).

7. Conclusions

The enhanced autonomous capabilities required in the most recent prototypes of UUVs make fault diagnostics and fault accommodation the subject of considerable attention. The present work considers the problem of diagnosing actuator faults on UUVs, and the results of the tests obtained with the Roby 2 UUV are presented. First, the importance of developing accurate models for the vehicles, without and with faults, must be stressed. The residuals are strongly affected by noise and by model uncertainty: the marine environment is a source of noises with unknown distribution, and a very simple decoupled model has been used. As far as this is concerned, improvements can be attained by modelling the environment (for instance, the presence of waves), and by using coupled models of the vehicle. Secondly, it appears to be fundamental task, to generate and evaluate residuals robust enough with respect to uncertainties in the models and in the measurements, by integrating all the available information on the vehicle status. All these improvements in the diagnostics for underwater vehicles will be crucial to the development of new UUVs with increased autonomous capabilities.

Future work will be devoted to the extension of the proposed fault detection scheme, with the target of attaining complete supervision of the performance of the vehicle, using other kinds of sensors and information on the vehicle subsystems. Another challenge for the future is the design of a fault-tolerant reconfigurable architecture, using redundant components, so as to replace the functionality of broken sensors, actuators, and electronic packages.

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