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IFAC PapersOnLine 55-6 (2022) 755–759

Actuator Fault Reconstruction via Dynamic Neural Networks for an Autonomous Underwater Vehicle Model

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Abstract: This paper proposes the development of a scheme for the fault diagnosis of the actuators of a simulated model accurately representing the behaviour of an autonomous underwater vehicle. The Fossen model usually adopted to describe the dynamics of the underwater vehicle has been generalised in this paper to take into account time–varying sea currents. The proposed fault detection and isolation strategy uses a data–driven approach relying on multi–layer perceptron neural networks that include auto–regressive exogenous prototypes that provide the fault reconstruction. These tools are thus exploited to design a bank of dynamic neural networks for residual generation that are trained on the basis of the input and output measurements acquired from the simulator. In this work, the residuals are designed to represent the reconstruction of the fault signals themselves. Moreover, the neural network bank is also able to perform the isolation task, in case of simultaneous and concurrent faults affecting the actuators. The paper firstly describes the steps performed for deriving the proposed fault diagnosis solution. Secondly, the effectiveness of the scheme is demonstrated by means of high–fidelity simulations of a realistic autonomous underwater vehicle, in the presence of faults and marine current.

Keywords: Fault diagnosis, fault estimation, neural network, actuator faults, robustness, autonomous underwater vehicle.

1. INTRODUCTION

Unmanned vehicles, and in particular Autonomous Underwater Vehicles (AUVs), have been widely used in many areas, such as photographing, monitoring traffic incidents, patrolling, and delivering etc. Since the tasks assigned to the UAVs are getting more and more complicated, the demand and requirement for the motion control of the UAV is also increasing. The common example of UAVs is multirotors which are mechanically simpler, and easier to control. We are seeing the increased utilization of multirotors for commercial applications. Since multirotors have many components such as motor, propeller, IMU sensors and some mechanical parts, the risk of performance losses caused by actuator or sensor faults is fast becoming a reality. The solution is to develop Fault Detection and Identification (FDI) and well as Fault Tolerant Control (FTC) solutions to to detect and accommodate these faults to maintain a certain level of performance for safety reason. The concept of FTC is not new. It can be defined as a controller that is able to tolerate faults and keep the control performance in an acceptable range in the presence of faults.

It is worth noting that this work is motivated by the Interreg Italy–Croatia SUSHI DROP project (Menghini et al. (2020)), where the authors are involved. In fact, the project is oriented to the design, the development and the validation of an AUV underwater biological and habitat researches.

FDI and PTC research activities applied to AUV FDI were based, for example, on the analysis of nonlinear dynamic structures exploited for residual generation and statistical change detection analysis (Falkenberg et al. (2014)). Other solutions used *e.g.* observer–based approaches (Antonelli (2018)), graph–theory–based analysis of the system structure (Blanke (2005)), fault estimators relying on extended Kalman filters (Alessandri et al. (1999)). Moreover, an exhaustive overview of FDI algorithms, specifically developed for AUVs, is addressed in (Antonelli (2003)).

This paper presents the results achieved via a data–driven methodology exploited for the design of a FDI scheme applied to the AUV actuators. The proposed approach was already exploited for the reconstruction of the fault affecting a wind turbine process, as described *e.g.* in (Simani and Farsoni (2018)). On the other hand, a different FDI strategy based on differential geometry tools was addressed in (Menghini et al. (2020)) and applied to

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10.1016/j.ifacol.2022.07.217

the same AUV simulator. The same solutions were also presented in (Castaldi et al. (2021)).

In this paper, it is presented an intelligent FDI scheme to deal with both actuator and sensor faults, where quadrotor is considered. The AI-based neural network learning is used for approximating unknown nonlinearities and faulty components in the AUV. The functionalities developed in this paper are:

- Fault diagnosis scheme able to handle both actuator and sensor faults
- Neural network for estimating the fault size for actuators
- Neural network trained to isolate actuator faults

The paper is organized as follows. After this short introduction, the representative model of the AUV is recalled. The neural network scheme and the fault estimation method are presented. The simulation studies are given to illustrate the proposed solutions. Concluding remarks end the paper.

2. MODEL SIMULATOR

The mathematical model implemented in the ODIN AUV simulator is based on the Fossen model. The AUV model is described as a rigid body with 6 DOF, whose dynamic relations are the standard ones comprising the translational motion of the Centre of Gravity (CoG) and the rotation around the CoG itself, *i.e.* the centre of the Body Frame (BF). The model consists of the above described dynamics and the related kinematics.

The main modules of the high fidelity ODIN AUV simulator implemented in the Matlab and Simulink environments are sketched in Figure 1.

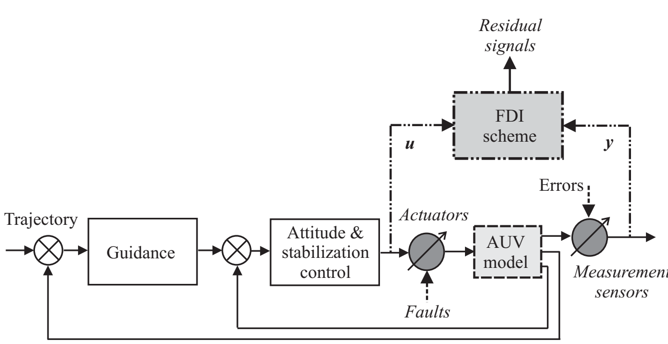

Fig. 1. The ODIN AUV simulator scheme.

The AUV simulator includes the effects of multiple and simultaneous faults affecting the actuator inputs, u_{th_i}, with $i = 1, \ldots, 6$, by using additive step function. They start at different times, from $0s.$ to $600s.$, with sizes from $5N$ to $50N$, which represents the maximum thrust value on the single actuator. In the following, the vector $\boldsymbol{u}(k)$ represents the control inputs acquired from the ODIN AUV simulator, and in particular $\boldsymbol{u}(k) = [u_1(k), u_2(k), u_3(k), u_4(k), u_5(k), u_6(k)]^T = [u_{th_1}(k), u_{th_2}(k), u_{th_3}(k), u_{th_4}(k), u_{th_5}(k), u_{th_6}(k)]^T$.

Furthermore, the monitored output vector $\boldsymbol{y}(k)$ is defined as $\boldsymbol{y}(k) = [y_1(k), y_2(k), y_3(k), y_4(k), y_5(k), y_6(k)]^T = [u, v, \omega, p, q, r]^T$. These signals will be exploited for FDI purpose, as described in Sections 3 and 4.

3. DATA–DRIVEN FAULT DIAGNOSIS

This section addresses the derivation of the fault diagnosis strategy, by recalling the basic features of the NNs. Moreover, when these static tools include ARX structures, they can be used as residual generators for solving the problem of the fault diagnosis, according to the analytical redundancy principle (Chen and Patton (1999)).

This work assumes that the process under diagnosis is affected by actuator faults and errors on the input and output measurements, as remarked in Section 2. These errors represent the effects of noise and uncertainty terms affecting the considered process under monitoring. Moreover, this work proposes to exploit NN structures to provide an on–line reconstruction $\hat{\mathbf{f}}(k)$ of the actual faults $\mathbf{f}(k)$ affecting the ODIN UAV actuators. Hence, the diagnostic residuals represent the estimation of the fault signals themselves, $\hat{\mathbf{f}}(k)$, as highlighted by Eq. (1):

$$\mathbf{r}(k) = \hat{\mathbf{f}}(k) \tag{1}$$

As it will be remarked in the following, the residual vector $\mathbf{r}(k)$ will be generated by a bank of dynamic NNs, which is designed to be selectively sensitive to the faults f_i affecting the process actuators.

Therefore, this solution allows both the fault detection and the fault isolation, as the bank of dynamic NNs is used to generate a set of dedicated residuals $r_i(k)$ representing the estimation of the faults f_i, *i.e.* $\hat{f}_i$. By a proper selection of the input and the output signals feeding the NNs, each residual signal $r_i(k)$ is designed to be selectively sensitive to a single actuator fault f_i. This residual generation strategy is depicted in Fig. 2.

According to the structure sketched in Figure 2, in order to uniquely isolate one of the actuator faults, a bank of Multi–Input Single–Output (MISO) residual generators is designed. In general, the number of these estimators is equal to the number of faults that have to be isolated, and in this case it coincides with the number of actuators p. Therefore, the i–th residual generator $r_i(k) = \hat{f}_i(k)$ in Figure 2 is properly driven by the components of the input and output signals $\mathbf{u}(k)$ and $\mathbf{y}(k)$, *i.e.* a set of measurements $u_j(k)$ and $y_l(k)$. These components are selected such that the i–th residual generator is the reconstruction of the specific fault $f_i(k)$.

For each fault case, the fault modes and their resulting effects on the measurements are analysed, and in particular the most sensitive input $u_j(k)$ and output $y_l(k)$ measurements to that specific fault situation are selected to feed the i–th dynamic NN. In this way, by means of the proposed NN tool, it will be possible to estimate the dynamic relations between the input–output measurements, $u_j(k)$ and $y_l(k)$, and the diagnostic residuals $r_i(k) = \hat{f}_i(k)$, as depicted in Figure 2. Moreover, using this strategy, also multiple and simultaneous faults occurring at the same or different times time can be correctly isolated.

Finally, as already remarked, the sensitivity analysis conducted before designing the residual generators, suggests

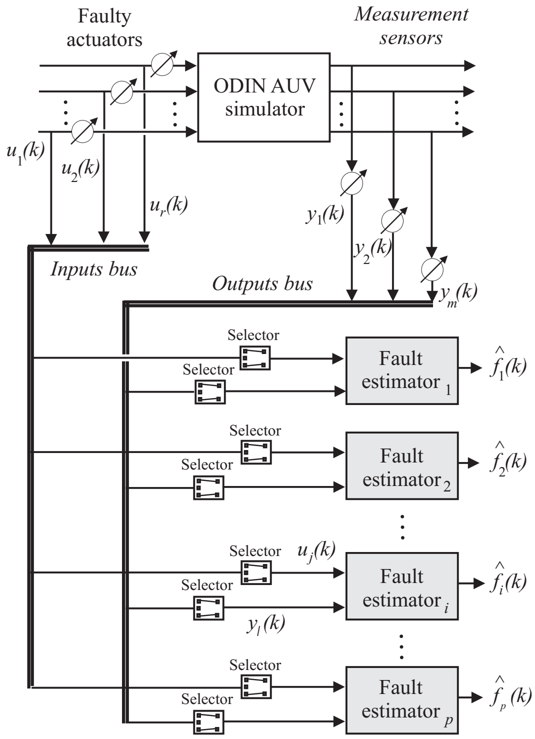

Fig. 2. Residual generator bank for fault reconstruction.

how to select the input–output signals feeding the dynamic NNs. After this selection, the training of the dynamic NN structures can be performed.

4. SIMULATION RESULTS

This sections illustrates the application of the FDI strategy summarised in the paper that is applied to the ODIN AUV simulator recalled in Section 2. In particular, on the basis of the results of the fault sensitivity analysis, which has led to the design of the bank of residual generators for FDI, Section 4.1 summarises the capabilities of the proposed fault diagnosis scheme, when different fault cases are simulated by means of the ODIN AUV simulator.

4.1 Fault Estimation Assessment

The proposed FDI scheme has been validated by using several simulations of the fault–free and faulty cases of the ODIN AUV simulator. The simulations included realistic measurement errors and the disturbance effect due to the Adriatic Sea marine current. The considered maximum sea current is equal to 1 kts. The direction of this current is along the x–y coordinate reference frame, *i.e.* the North–East direction, while the component along the z coordinate is not considered, as a sufficient depth is assumed for the AUV to neglect it.

As described in Section 3, the FDI scheme consists of a bank of 6 residual generators. The first simulations considered the case of single fault on the 1$^{\text{st}}$ actuator that has been injected by adding a step function to the considered input u_{th_1}. Therefore, the fault commences at $t = 150s$. with a size of $5N$, when the maximum thrust generated by the single actuators is $50N$.

In particular, the 6 NARX residual generators have been implemented as MLP NNs with 3 layers: the input layer consisted of 3 neurons, the hidden one used 10 neurons, whilst one neuron for the output layer. A number of $d_u = d_y = 3$ delays has been used in the neural network design; moreover, sigmoidal activation functions were used in both the input and the hidden layers, and a linear function for the output layer. These parameters were selected via a trial and error procedure in order to achieve the best performances.

Figure 3 depicts the behaviour of the residual signals $r_i(k) = \hat{f}_i(k)$ in case of single actuator fault. It is worth noting that the signal corresponding to the first residual $r_1(k)$ reconstructs the fault $f_1(k)$, whilst the remaining residuals $r_j(k)$ with $j \neq 1$ are not affected by this fault, according to the design procedure addressed in Section 3 and with the signal selection.

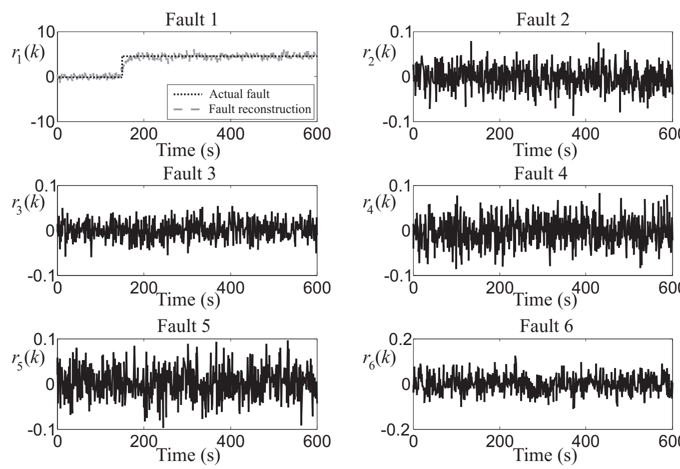

Fig. 3. Residuals for the case of the actuator fault $f_1(k)$.

It is worth noting that the designed FDI scheme seems to be robust with respect to the sea current, with an adequate minimum detectable fault size, which allows also the fault isolation, as highlighted in Figure 3. Furthermore, the limited detection delay time makes the designed FDI scheme suitable to the early diagnosis of single faults acting on the UAV.

As further example, the case of constant step fault of $5N$ on the 4$^{\text{th}}$ actuator, *i.e.* u_{th_4}, is injected into the simulator at $t = 150s$. Figure 4 reports the residual signals, thus highlighting that only the residual $r_4(k)$ represents the estimation of the actuator fault $f_4(k)$, whilst the remaining residual signals $r_j(k)$ with $j \neq 4$ are almost zero.

In order to validate the proposed FDI scheme in the presence of simultaneous faults, two concurrent faults are injected into the system actuators, and in particular:

- the step fault f_3 affecting u_{th_3} at $t = 150s$;
- the step fault f_5 affecting u_{th_5} at $t = 300s$.

Figure 5 shows the effectiveness of the residual generator bank designed according to the procedure exploited in the work. In fact, only the residual signals $r_3(k)$ and $r_5(k)$ correspond to the reconstruction of the faults $f_3(k)$ and $f_5(k)$, respectively. Therefore, the concurrent faults affecting the actuator signals u_{th_3} and u_{th_5} can be also isolated.

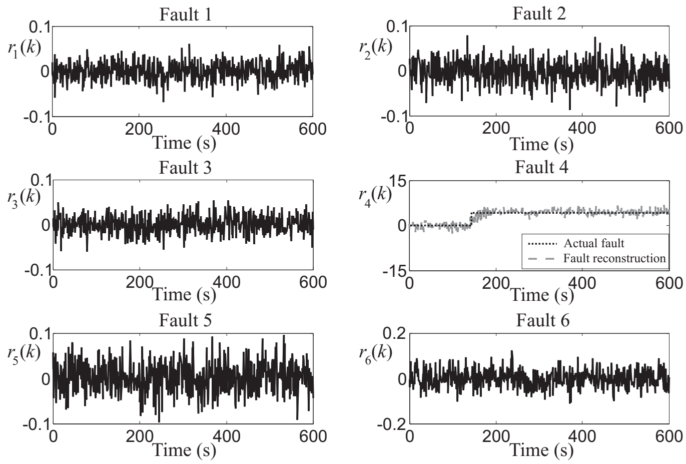

Fig. 4. Residuals for the case of the actuator fault $f_4(k)$.

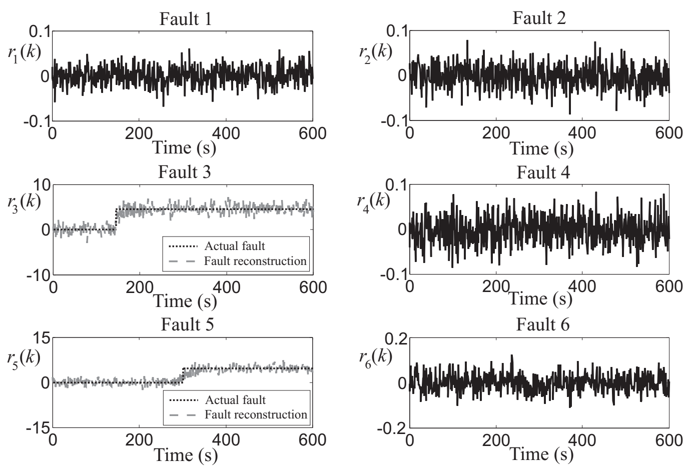

Fig. 5. Residuals for the case of the actuator faults $f_3(k)$ and $f_5(k)$.

Finally, the capabilities of the FDI scheme are summarised in Table 1 by reporting the size of the minimal detectable faults f_i that are injected into the actuator signals u_{th_i} of the ODIN AUV simulator. The accuracy in the reconstruction of the fault signals is also reported, computed as percent normalised root mean squared error in the form of (2):

$$100 \times \frac{\sqrt{\sum_{k=1}^{N} \left(f_i(k) - \hat{f}_i(k) \right)^2}}{\sqrt{\sum_{j=1}^{N} f_i^2(k)}} \tag{2}$$

with reference to the i–th fault and computed over N samples.

Table 1. Minimal detectable faults on the actuator signals u_{th_i} and their reconstruction errors.

Fault Case	Minimum Fault Size	Reconstruction Error
f_1	$5N$	1.97%
f_2	$2N$	2.05%
f_3	$3N$	2.16%
f_4	$4N$	1.89%
f_5	$5N$	2.08%
f_6	$3N$	1.99%

The results reported in Table 1 highlight that the performances of the designed FDI scheme are quite accurate despite of the disturbance and the uncertainty included in the ODIN UAV simulator, and thus motivate the application of the developed fault diagnosis strategy to real UAV systems. Further investigations will focus on the evaluation of the detection delays and the use of the estimated fault signals for fault tolerant applications of the considered data–driven methodologies. Moreover, other fault scenarios and different uncertainty and disturbance conditions will be also considered in order to verify and validate the proposed fault diagnosis strategy.

5. CONCLUSION

This paper addressed the development of a data–driven fault diagnosis scheme relying on multi–layer perceptron neural networks that include auto–regressive exogenous structures. The fault diagnosis scheme was applied to a high–fidelity simulator of the omni–directional intelligent navigator autonomous underwater vehicle based on a Fossen model. The developed fault diagnosis strategy led to a bank of dynamic neural networks that were able to estimate single and simultaneous faults affecting the model actuators. The simulations performed by using the high–fidelity simulator served to verify the performance of the developed fault diagnosis approach. The dynamic neural networks of the bank that provided a dedicated residual set were trained offline by using the input and output measurements acquired from the simulator. On the other hand, the designed tool was obtained in a straightforward way, and it did not require complex analytical computations. It is also suitable for real–time implementations and it can be especially oriented to safety–critical systems requiring a high level of reliability and availability. Further works will verify the features of the proposed data–driven schemes for real autonomous underwater vehicles, and applied also for fault tolerant control strategies. Other fault scenarios and different uncertainty and disturbance conditions will be also considered in order to further verify and validate the proposed fault diagnosis strategy.

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