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Sensor and actuator fault detection in small autonomous helicopters

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Abstract

The use of autonomous helicopters in civilian applications requires the improvement of safety conditions to avoid potential accidents. Fault detection and isolation (FDI) plays an important role in this context. This paper presents an actuator and sensor FDI system for small autonomous helicopters. Fault detection is accomplished by evaluating any significant change in the behaviour of the vehicle with respect to the fault-free behaviour, which is estimated by using observers. Several types of faults have been considered. The effectiveness of the proposed approach is demonstrated by means of experimental results and simulations.

Keywords: Fault detection and identification; Autonomous helicopters; UAV; Actuators; Sensors

1. Introduction

Unmanned aerial vehicles are increasingly used in many applications in which ground vehicles cannot access to the desired locations due to the characteristics of the terrain and the presence of obstacles. In many cases the use of aerial vehicles is the best way to approach the objective to get information or to deploy instrumentation.

Helicopters have high manoeuvrability and hovering ability. Then, they are well suited to agile target tracking tasks, as well as to inspection and monitoring tasks that require to maintain a position and to obtain detailed views. Furthermore, the vertical take-off and landing capabilities of helicopters is very desirable in many applications. Remotely piloted helicopters are inherently unstable and dynamically fast. Even with improved stability augmentation devices, a skilled, experienced pilot is required to control them during flight. Autonomous helicopter control is a challenging task involving a multivariable non-linear open-loop unstable system with actuator saturations.

Moreover, helicopters do not have the graceful degradation properties of fixed wing aircrafts or airships in case of failures. Thus, a failure in any part of the autonomous helicopter (actuators, sensors, control system, etc.) can be catastrophic. If the failure is not detected and accounted for, the helicopter may crash.

Fault detection and isolation (FDI) techniques have been widely used in process industry to detect faults in actuators and sensors. If a fault is detected, the structure of the controller can be changed to get the best possible response of the system, or even the system can be brought to an emergency stop.

Fault detection approaches can be classified as model-free and model-based paradigms. 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.

From the beginning of the seventies, there have been numerous theoretical advancements in fault diagnostics based on analytical redundancy (see, for example [1] for a recent survey). 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.

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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 different ways: parity equations [2], observer-based generation [3], and the methods based on parameter estimation [4]. Neural networks and fuzzy systems have also been applied in model-based FDI [5].

Observer-based and parameter estimation methods are the most frequently applied methods for fault detection [6]. Most published work in recent years on FDI systems for autonomous vehicles also use observer-based methods. The basic idea behind the observer or filter-based approach is to estimate the outputs of the system from the measurements by using either Luenberger observer(s) in a deterministic setting or Kalman filter(s) in a stochastic setting.

Particularly in the field of autonomous vehicles FDI, Luenberger observers, Kalman filters, banks of observers and Kalman filters and neural networks have been used for observer generation. Neural networks have been used to detect sensor and actuator faults applied to a B-747 mathematical model [7]. A bank of Kalman filters and neural networks have also been used for sensor fault detection on a NASA high altitude UAV simulation model [8], and on B-373 actual flight data [9]. A bank of Kalman filters have been also used for fault detection in aircrafts [10]. Actuator fault detection in unmanned underwater vehicles has been done using a bank of Kalman filter estimators [11].

However, very few results on fault detection for autonomous helicopters can be found in the literature. Drozeski et al. [12,13] present a FDI system based on neural networks in the context of a reconfigurable flight control architecture for UAVs. The FDI system has been implemented and tested in a modified Yamaha RMAX autonomous helicopter (the RMAX airframe weighs 58 kg, and has a 30 kg payload).

In this paper, the diagnosis of actuator and sensor faults in autonomous helicopters is investigated and the design of a fault detection system is considered, using a model-based approach, with observer-based residual generation. The system is tested with real flight data. This paper is based on conference papers [14,15].

The paper is organized as follows. Small autonomous helicopters are described in Section 2. Section 3 introduces the fault detection and isolation approach. The results on the application of these techniques to actuator and sensor fault detection are presented in Sections 4 and 5, respectively. Section 6 is devoted to the conclusions.

2. Small autonomous helicopters

Several small autonomous helicopter prototypes have been developed in recent years at different research centres throughout the world [16]. In most cases, the prototype is built upon a commercial airframe, to which sensors, computers and communication equipment are added. In many cases the airframe is a conventional model helicopter (see, for example, the MARVIN helicopter [17], or the AVATAR helicopter [18]). The payload is usually around 4–8 kg, and therefore the equipment that can be mounted onboard is limited. In some cases, the Yamaha RMAX spraying helicopter is used as airframe (see for example the GTMax [12,13]). The RMAX is larger than the other airframes (the payload is around 30 kg) and it does not have these weight limitations.

Small helicopters typically have five control inputs: collective pitch p_c, cyclic pitch p_y for pitching, cyclic pitch p_x for rolling, tail rotor pitch p_{tr} and engine throttle p_t. It is usual that an engine governor or a separate throttle control loop maintain the speed of the main rotor at a constant value manipulating the throttle p_t, and therefore the flight controller control only the four first inputs.

Helicopters have linkages in the main rotor system that mechanically relates the helicopter's blade angles to the main rotor actuators, via an intermediary swashplate. Most small helicopters usually have three swashplate actuators, but in some cases four actuators are used [17].

If one of the main rotor actuators fails, severe degradation or even complete loss of helicopter controllability may happen. In these situations, fast and reliable detection and identification of the fault is very important. Once the information of the presence and location of the failure is available, the flight system can take actions to counteract its effects via controller reconfiguration. Enns and Li [19] propose an actuator geometry for three-actuator swashplates that provides control axis coupling and a reconfiguration strategy that retain control of any two of the three control axes at a time. Drozeski et al. [13] present a reconfigurable flight control architecture that recovers vertical control after a collective actuator fault in a helicopter, controlling the speed of the main rotor with the throttle p_t.

Helicopter autonomous flight needs precise position and attitude information for control and stabilization. Small autonomous helicopters carry a pack of sensors that in a typical case includes an inertial measurement unit (IMU) with three gyros, three accelerometers and three-axis magnetometer for attitude determination, a centimeter-precision kinematic DGPS, a sensor for measuring the main rotor rpm, and an ultrasonic altitude sensor for take-off and landing.

A fault in one of the sensors, although not as crucial as actuator faults, may induce position and attitude estimation errors if undetected. Reconfiguration in these cases usually consists in isolating the faulty sensor and using the other sensors to get the best possible estimation of position and attitude.

Some of the experimental data presented in this paper has been recorded using the MARVIN helicopter [17], which is based on a conventional model airframe (see Fig. 1). Sensors for position and attitude determination include an IMU, an ultrasonic rangefinder looking down and a Novatel RT-2 carrier phase differential GPS receiver.

MARVIN's actuators are six servos that operate the engine throttle, the tail rotor pitch, and the main rotor pitch settings. The swashplate is moved by four servos,

Fig. 1. MARVIN helicopter in flight.

which control its position and orientation at one of four corners with 90° offset. This means that three parameters (collective pitch p_c, cyclic pitch p_y for pitching, and cyclic pitch p_x for rolling) are redundantly affected by four servo outputs, the front servo s_f, the rear servo s_b, the left servo s_l, and the right servo s_r. The involved relations are:

$$p_c = \frac{1}{4}(s_f + s_b + s_l + s_r)$$
$$p_x = s_l - s_r$$
$$p_y = s_b - s_f$$

The servo signals have to be calculated by the controller according to the above relations. Consequently, if one of the servos fails but can be moved by the remaining three, MARVIN can still operate safely without any special measures. Thus, early fault detection and identification is relevant to increase helicopter safety.

3. Fault detection and identification

3.1. Introduction

Safety and reliability are important requirements in man-made dynamical systems. These requirements apply specially to safety-critical systems, as is the case of helicopters. The early detection of faults can help to avoid system shut-down, breakdown and even catastrophes involving human and material damage.

The monitoring of faults in feedback control system components is known as fault detection and isolation (FDI). The procedure of generating a control action which has a low dependency on the presence of certain faults is known as fault tolerant control.

Fig. 2 shows the general schematic arrangement appropriate to many fault tolerant control systems [20] with four main components: the plant itself (including sensors and actuators), the FDI unit, the feedback controller and the supervision system. The plant is considered to have potential faults in sensors, actuators or other components. The FDI unit provides the supervision system with information about the onset, location and severity of any fault. Based on system inputs and outputs together with fault decision information from the FDI unit, the supervision system will reconfigure the sensor set and/or actuators to isolate the faults, and tune or adapt the controller to accommodate the fault effects.

The FDI unit is a basic element of the fault tolerant control scheme presented in Fig. 2. The work presented in this paper concentrates on FDI. The scheme used for fault identification is presented in Fig. 3, where **u** and **y** are the inputs and outputs vectors of the autonomous helicopter, respectively. The observer block is an input–output model of the helicopter in nominal fault-free conditions, obtained by system identification. The output of the observer is an estimation of the output of the helicopter, $\mathbf{y}_{est}$. The residuals **R** are generated comparing the estimated outputs of the helicopter with the actual outputs. If a fault is present in the system, the fault diagnosis system will analyse the generated residuals to detect and isolate the fault.

Helicopters are non-linear coupled multiple-input, multiple-output (MIMO) systems. However, when dealing with non-aggressive flight scenarios, such as hovering, up-down and forward–backward flights, a linear model can be sufficient for many applications. Furthermore, the models are used in FDI for prediction in the short term of helicopter position and orientation and sensor outputs.

In any case, as the flight data used for identification do not cover the whole flight envelope for security reasons in

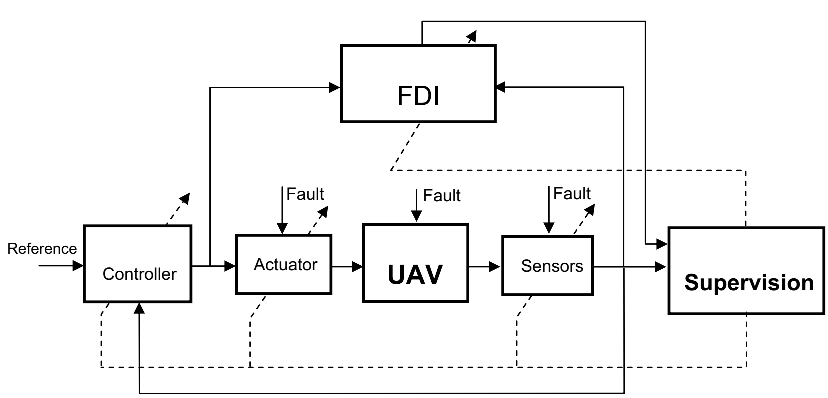


Fig. 2. Scheme of fault tolerant control system with supervision subsystem.

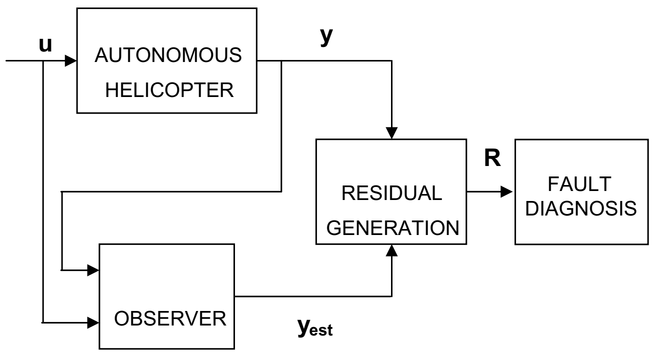


Fig. 3. Fault identification scheme.

the experiments, the designed FDI system checks that the flight conditions are within the values of some variables used for identification. If the FDI system detects a fault when one of these variables is outside the specified range, the FDI system will issue a warning, but it has to confirm the fault declaration after the warning when the flight variables are inside the specified range.

The variables used to specify the flight envelope covered by the identification data and the limit values are the helicopter velocity in the XY plane in world coordinates ($\mathrm{Vel}_{XY} < 10$ m/s), the vertical helicopter velocity in world coordinates ($\mathrm{Vel}_Z < 2$ m/s), the helicopter pitch angle (Pitch < 20°) and the helicopter roll angle (Roll > 10°). Fig. 4 shows helicopter velocities in a typical experiment used for identification.

From a practical perspective, a FDI system based on linear observers is easier to implement on board small autonomous helicopters, which usually have limited computing resources. Linear observers have been used in this paper for fault detection.

3.2. Observer design

For FDI purposes, the estimation of the state vector is unnecessary and only output estimation is required [3]. Therefore, an input–output model of the helicopter system can be identified for output prediction. Since past inputs and outputs are available to the FDI system at any given instant, the input–output model can be used to estimate the actual output in fault-free conditions. A linear mathematical model of the input–output links can be used for local analysis. This model can be obtained by means of well known identification schemes.

In case of high signal to noise ratios, equation error identification can be exploited and, in particular, different equation error models can be extracted from the data. A specific discrete-time, time-invariant, linear dynamic model, e.g. ARX or ARMAX (Auto Regressive eXogenous or Auto Regressive Moving Average eXogenous), can be selected inside an assumed family of models.

A number of ARX Multi-Input Single-Output (MISO) models have been identified for FDI. These models are of the type:

$$y_i^*(t) = \sum_{j=1}^{n} \alpha_{i,j} y_i^*(t-j) + \sum_{j=1}^{r} \sum_{k=1}^{n} \beta_{i,j,k} u_j^*(t-k) + \varepsilon_i(t) \qquad (1)$$

The number of identified MISO ARX models is equal to the number m of the output variables. The model order n and the parameters $\alpha_{i,j}$ and $\beta_{i,j,k}$ with $i = 1,\ldots,m$, of the model have to be determined by the identification approach. The term $\varepsilon_i(t)$ takes into account the modelling error, which is due to process noise, parameter variations, etc.

The ARX model is chosen with the structure that achieve the smallest Akaike's Information Theoretic Criterion (AIC) [21], according to a simple search algorithm, in which the first half of data is used for estimation and the second for cross-validation.

3.3. Input–output data for model identification

High quality flight data are essential to a successful identification. The main concerns are the accuracy of the

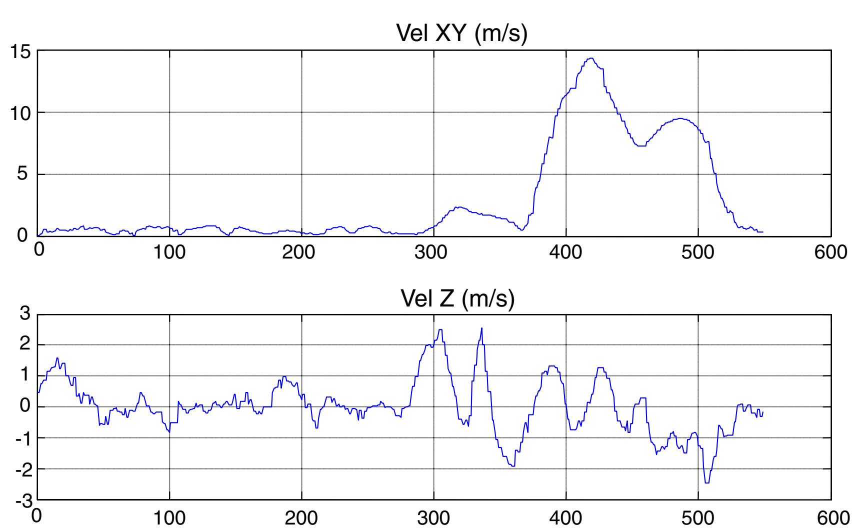
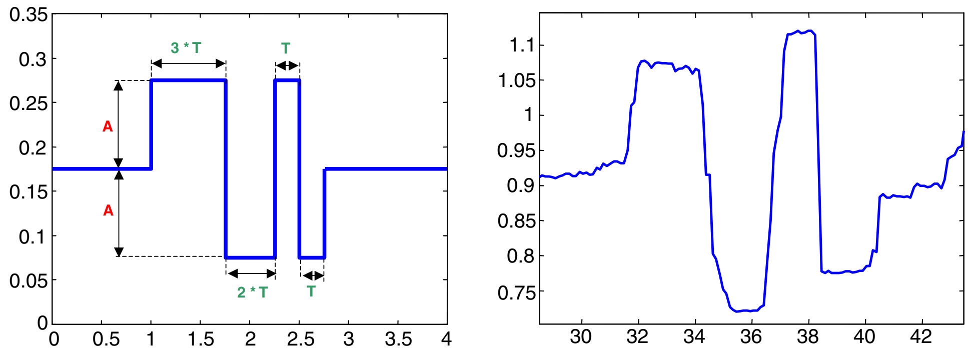


Fig. 4. Helicopter velocities in a typical experiment.



a) 3211 input signal definition. b) 3211 real input signal in a sample experiment.

Fig. 5. (a) 3211 input signal definition and (b) 3211 real input signal in a sample experiment.

estimated vehicle states and the information content of the flight data (i.e., whether the measurements contain evidence of the relevant vehicle dynamics).

The system identification has been performed using input–output data taken by flying the helicopter in a way to obtain evidences of the relevant vehicle dynamics. The only realistic way to obtain these data is to perform special purpose experiments with the helicopter. In these experiments, that were done open-loop by a human pilot, an input sequence was used in one of the inputs of the helicopter, while maintaining almost constant the other inputs (these inputs were modified slightly by the pilot to maintain stability if needed).

Input sequences that are normally used in aircraft and helicopter identification include the doublet signal and the 3211 input signal. The 3211 input sequence (shown in Fig. 5a) has been used in the identification experiments because it has higher frequency content while still being easily reproduced by the pilot. Fig. 5b shows the corresponding real input signal generated by the human pilot in a sample experiment.

4. Actuator fault detection

The helicopter actuator fault detection system has been designed and tested using flight data from two different sources: A full non-linear mathematical model and real flight data obtained from the MARVIN helicopter.

The mathematical model includes rigid body dynamics, actuator dynamics, and force and moment generation dynamics, including the flybar. This model is similar to the one presented by Kim and Tilbury [22]. The parameters of the model have been identified with the MARVIN helicopter.

The use of the mathematical non-linear model makes easier to test the actuator fault detection system, because datasets can be easily generated by computer simulation as needed. On the other hand, real flight experiments are the best way of testing the fault detection system, although it is more expensive and time consuming, and they are not available at any time.

4.1. Fault detection using simulated helicopter data

Flight data obtained by simulation of the full non-linear model have been used to detect faults in all four helicopter actuators: main rotor collective, tail rotor collective and both rolling and pitching cyclic inputs.

In Fig. 6, the results of a collective actuator fault detection is shown. The upper graph shows the real helicopter vertical linear velocity Vz. The middle graph shows the Vz estimated by the observer. The lower graph shows the evolution of the calculated residual. At $t = 5$ s, the collective actuator gets stuck near the trim hovering value. It can be seen that as a result of the collective failure, the helicopter Vz remains almost constant while the Vz estimated by the observer varies. This is captured by the residual evolution, which is below the threshold level for fault-free operation but exceeds the threshold value (dashed line) after the

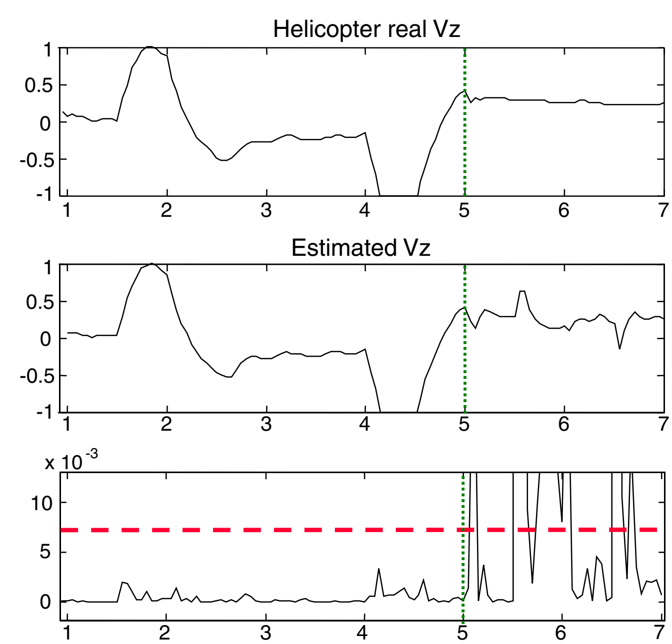


Fig. 6. Collective fault detection (non-linear mathematical model).

actuator gets stuck, and therefore the collective fault can be detected.

Fault detection of the rolling cyclic actuator is presented in Fig. 7. The three plots show the real helicopter linear velocity Vx, the Vx estimated by the observer and the evolution of the rolling cyclic residual, respectively. At $t = 5$ s, the rolling cyclic actuator gets stuck near the trim hovering value. In this case, the detection time is larger, but this is due to that the cyclic input is not excited. In fact, it is impossible to detect an actuator failure if the actuator is not excited. In this experiment, the rolling cyclic actuator is not immediately excited, but after a few tenths of a second. Once the cyclic input is excited, the residual goes above the threshold value, and the fault can be detected.

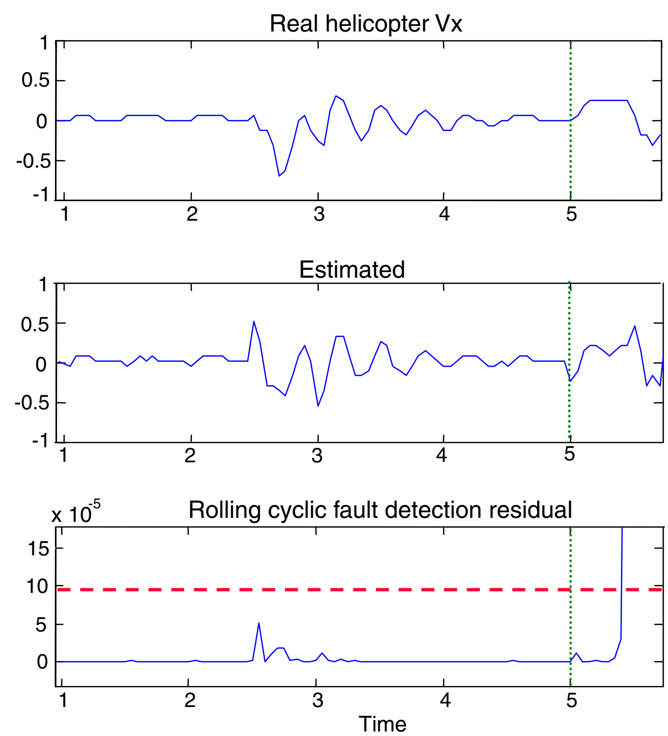


Fig. 7. Rolling cyclic fault detection (non-linear mathematical model).

4.2. Fault detection using real flight helicopter data

A failure in an actuator can be potentially dangerous for the helicopter, because it can take the helicopter out of control and it may crash. Even for experienced pilots, it could be dangerous to make flight experiments with a faulty actuator. In order to test the FDI system of the autonomous helicopter in real flight conditions, some experiments were planned to simulate a faulty condition in an actuator while maintaining security of people and the helicopter.

In these experiments, the pilot was commanded to make a flight with different movements, but at a given time, he should maintain one of the actuators almost fixed in a given position, and thus simulating a stuck actuator. These experiments were repeated in different flight conditions (near hover, forward flight at different velocities, etc.). Fig. 8 shows a photograph of the experiments. The video sequences can be seen in the COMETS web site (http://www.comets-uavs.org).

After the experiments, the input data was modified. The input signal corresponding to the "stuck" actuator was changed, and a different input command was introduced for that actuator. The effect of this modification is that a varying input signal is commanded to the helicopter, but, because of the stuck actuator, the actuator remains in a fixed position, and all the sensor data correspond to this stuck situation. This is an effective and safe way of reproducing faulty conditions in helicopter actuators.

In Fig. 9, an example actuator fault experiment is presented. A stuck type fault has been reproduced in the main rotor collective of the MARVIN helicopter, using real flight experiment data. At $t = 18$ s (dashed line) the collective actuator gets stuck. Then the collective input commanded by the controller cannot be followed by the actuator, which remains stuck (effective input line in Fig. 9).

The collective residual generated by the FDI system can be seen in Fig. 10. It can be seen that the residual is below the threshold level (horizontal dashed line) for normal fault-free operation. But, when the actuator gets stuck (vertical dashed line), the residual goes above the threshold level, and therefore, a collective actuator fault has been detected.

Fig. 8. MARVIN fault detection experiments.

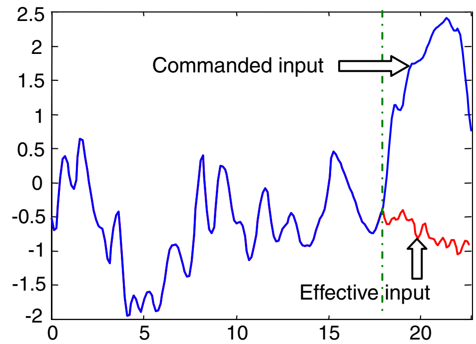


Fig. 9. MARVIN main rotor collective actuator failure.

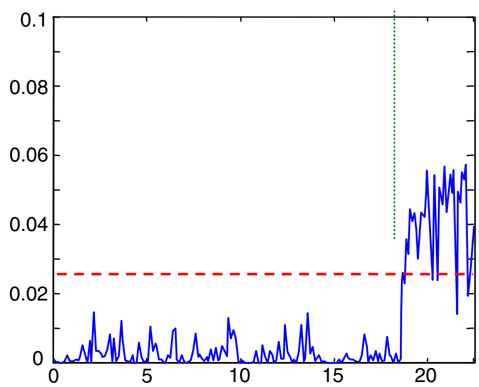


Fig. 10. Time evolution of the collective residual.

5. Sensor fault detection

5.1. Sensor fault detection structure

The helicopter sensor FDI subsystem performs the tasks of failure detection and identification by continuously monitoring the outputs of the sensors. Under nominal conditions, these measurements follow predictable patterns, within a tolerance determined by the amount of uncertainties introduced by random system disturbances and measurement noise in the sensors. Usually, sensor FDI tasks are accomplished by observing when the output of a failed sensor deviates from its predicted pattern.

For detection of faults in the helicopter sensors, a bank of output estimators has been implemented as showed in Fig. 11. This type of diagnosis system is usually called the dedicated observer scheme [23]. The number of these observers is equal to the number of system outputs. Thus, each device is driven by a single output and all the inputs of the system. In this case a fault on the ith output sensor affects only the residual function of the output observer or filter driven by the ith output. Therefore sensor faults can be isolated by analyzing the pattern of zero and nonzero residuals.

A residual is generated for each sensor, comparing the estimator output with the sensor output. Each residual is not affected by the other sensors, and therefore fault identification is straightforward: each residual is only sensitive to a single helicopter sensor. If the residual k goes above the threshold level, a fault has been detected in sensor k.

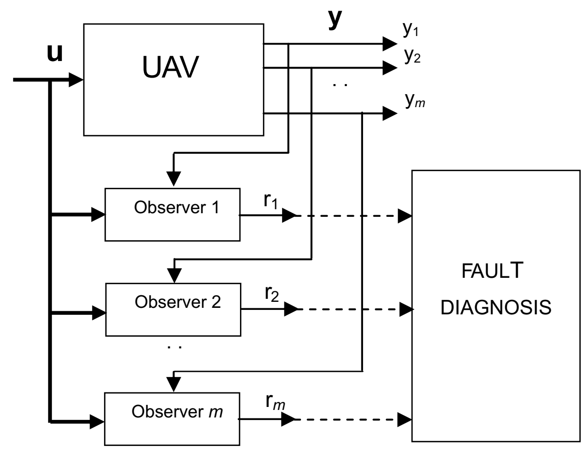


Fig. 11. Bank of estimators for output residual generation.

The sensor FDI system has been implemented with the above structure using ARX input–output models. The results are presented in the following subsections.

5.2. Sensor failure types

In this section, the results of helicopter sensor FDI system using linear ARX output estimators are presented. All the experiments have been done using real helicopter flight data. Flight data were recorded from several experiments carried out at the Lousá (Portugal) airfield during the general experiments of the COMETS project. These experiments were performed in spring with temperatures around 20 °C and low wind conditions.

Sensors used in autonomous helicopters can fail in several ways. Some failure types are general for various sensors, while others are specific of a single sensor. The failure types that have been considered in this work are the following:

- *Total sensor failure*. This is a catastrophic failure, at a given time the sensor stops working and gives a constant zero output after that. This failure can be due to electrical or communication problems.
- *Stuck with constant bias sensor failure*. In this failure type, at a given time the sensor gets stuck with a constant bias, and the output remains constant.
- *Drift or additive-type sensor failure*. This is a very common failure in analog sensors. Due to internal temperature changes or calibration problems, the sensor output has an added constant term (the drift).
- *Multiplicative-type sensor failure*. In this failure type, a multiplicative factor is applied to the sensor nominal value.
- *Outlier data sensor failure*. This is a failure that appears sometimes in GPS sensors. It is a temporal failure: a single point with a large error is given by the GPS sensor,

but after that, the following measurements are correct. This is supposed to be caused by failures in the GPS internal signal processing algorithms.

The MARVIN helicopter has 12 individual sensors: three gyroscopes, three accelerometers, three components of the magnetic sensor and the three GPS coordinates. Since there are too many possible combinations of sensors and failure types, only a few representative cases will be described in detail in this section.

The z component of the gyroscope angular velocity sensor will be used as representative case of sensor failure detection for the first four failure types presented (total sensor failure, stuck with constant bias, additive type and multiplicative type). The z component of the GPS sensor will be used for the fifth failure type (outlier data), since it is a specific failure of GPS sensors.

For some failure types, a sensor failure detectability study for all 12 MARVIN sensors has been conducted. Sensor failures have been studied in nine different helicopter experiments, using real MARVIN flight data. The results have been summarized in tables, including the detection time.

5.3. Stuck with constant bias sensor failure detection

The sensor fault has been reproduced using real flight data. In this case, the gyro-z sensor output gets stuck with the last output value before the fault was produced. In Fig. 12, there is a fault in the gyro-z sensor at $t = 18$ s (upper plot). It can be seen that, shortly after the fault, the residual goes above the threshold level (dashed line) and the fault is detected (lower plot).

This type of sensor fault, as well as the total sensor failure, can be easily detected by the FDI system. The faults have been successfully detected in all sensors and all experiments.

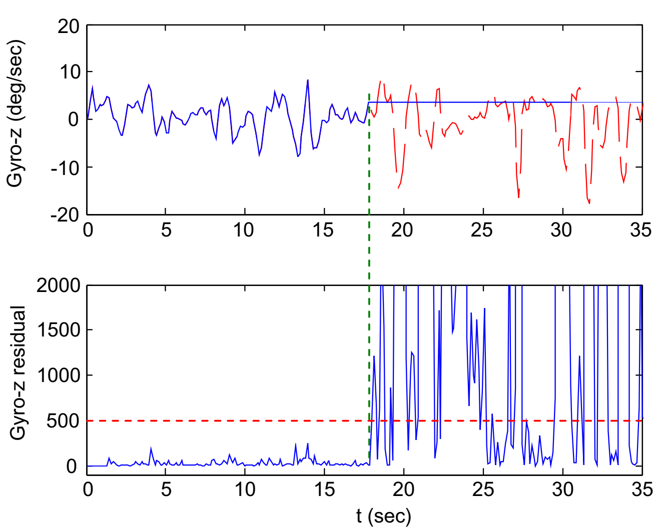


Fig. 12. Stuck with constant bias gyro-z failure detection.

5.4. Additive-type sensor failure detection

Figs. 13 and 14 show the results of the fault detection of additive faults in gyro-z sensor output. In Fig. 13, a 3.5°/s drift has been added, and the residual detects the fault very fast. In Fig. 14, a 1.75°/s drift has been added to the sensor output at $t = 18$ s.

A detectability study has also been done with the additive type sensor failure. Two cases have been considered: a drift of 50% of the maximum sensor value, which results are presented in Table 1, and a drift of 10% of the maximum sensor value, which results are presented in Table 2.

The results presented in Table 1 show that a drift 50% of maximum sensor value can be detected reliably in all the experiments. It can be noticed that the detection time is very short. The detection time means the time between the first erroneous measurement and the failure detection, excluding the processing time.

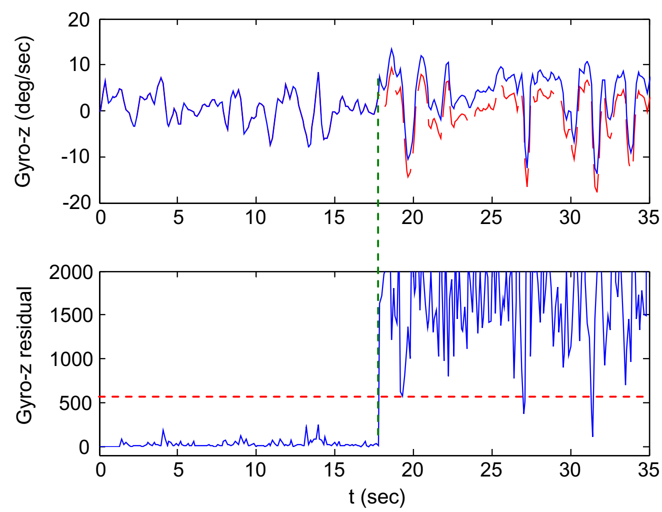


Fig. 13. Additive gyro-z sensor failure detection (drift of +3.5°/s).

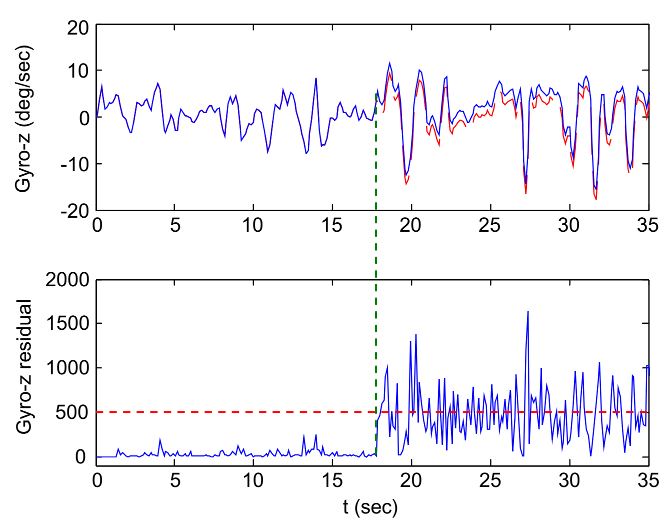


Fig. 14. Additive gyro-z sensor failure detection (drift of +1.75°/s).

Table 1
Sensor fault detection with drift of 50% of maximum sensor value

	GPS			ACCEL			MAG			GYRO		
	X	*Y*	*Z*	*X*	*Y*	*Z*	*X*	*Y*	*Z*	*X*	*Y*	*Z*
Mean detection time	0.00	0.00	0.00	0.00	0.00	0.09	0.09	0.00	0.00	0.12	0.00	0.00
Undetected faults	0	0	0	0	0	0	0	0	0	0	0	0
False alarms	0	0	0	0	0	0	0	0	0	0	0	0

Table 2
Sensor fault detection with drift of 10% of maximum sensor value

	GPS			ACCEL			MAG			GYRO		
	X	*Y*	*Z*	*X*	*Y*	*Z*	*X*	*Y*	*Z*	*X*	*Y*	*Z*
Mean detection time	0.15	3.67	0.00	0.75	2.42	0.75	0.14	0.00	0.00	0.75	3.25	0.90
Undetected faults	0	0	0	0	0	1	0	0	0	2	2	1
False alarms	0	0	0	2	0	3	3	0	0	0	1	0

On the other hand, the results of Table 2 shows that a 10% drift is much harder to detect. There is a number of undetected faults and false alarms, making the detection of this kind of faults unreliable. Detection times are also larger. Minimum detectable drift errors depend on the specific sensor, but are between 7% and 16% of maximum sensor value.

5.5. Outlier data sensor failure detection

This is a failure that appears in GPS receiver data. It is a single data point with large error. Fig. 15 shows the GPS sensor z data. At $t = 18$ s, the output has a 1 m error added. The fault is easily detected, due to the precision of MARVIN GPS sensor data.

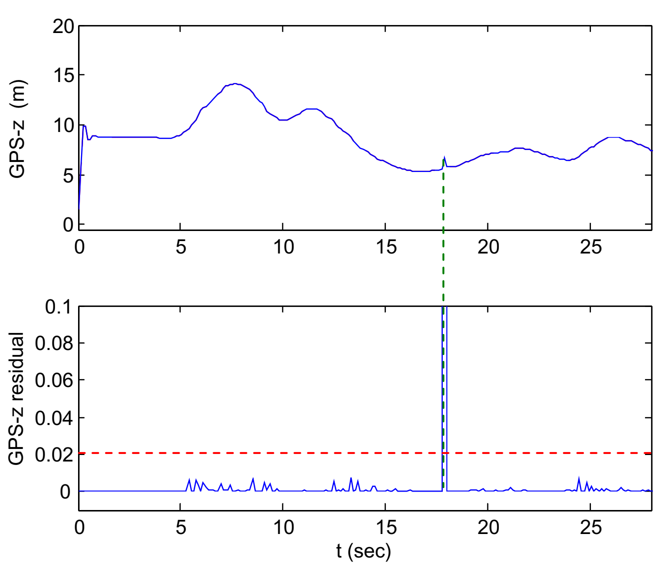


Fig. 15. Outlier data GPS-z sensor failure detection using ARX output estimator (1 m).

6. Conclusions

The use of autonomous helicopters in civilian applications requires the improvement of safety conditions to avoid potential accidents. Fault detection and isolation plays an important role in this context. This paper has presented a system for actuator and sensor fault detection in small autonomous helicopters. The system has been designed by using real flight experimental data. Extensive experiments with an autonomous helicopter have been conducted to collect input–output data in many different conditions. Actuator fault detection has been implemented for stuck actuator type failure. The effectiveness of the proposed approach is demonstrated by means of experimental results and simulations. Five different sensor failure types have been considered. "Hard" failures (zero or constant sensor output) are easily detected by the fault detection system in short time. "Soft" failures (sensor output with additive or multiplicative error) are detected depending on the error size. If errors are too small, they cannot be distinguished from noise. Outlier data sensor failures, typical of GPS receivers, are also easily detected. This can be combined with GPS signal quality measures that are reported by many GPS receivers to improve position estimation reliability.

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