Development of the Sensory Network for the Vibration-based Fault Detection and Isolation in the Multirotor UAV Propulsion System

Adam Bondyra, Przemysław Gąsior, Stanisław Gardecki and Andrzej Kasiński
Institute of Control, Robotics and Information Engineering,
Poznan University of Technology, Piotrowo 3A, Poznan, Poland

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Abstract: In this paper, a fault detection and isolation (FDI) system for propeller impairments of the multirotor UAV is presented. The algorithm is based on the processing of signal vectors from the set of vibration sensors located close to the propulsion units. Axial and radial vibrations are measured using MEMS accelerometers that provide data for the feature extraction based on the Fast Fourier Transform (FFT). Characteristic fault signatures extracted from vibration signals are used to detect and localize damaged blades using the set of random decision trees. A method was evaluated with data gathered during numerous test flights and validated in relation to signal acquisition time and number of classifiers in the ensemble. Results show over 95% sensitivity in detecting and isolating faulty rotor states. The presented approach is an effective and low-cost solution, very versatile to implement in the arbitrary UAV.

1 INTRODUCTION

An increasing popularity of micro multirotor unmanned aerial vehicles leads to concerns regarding the safety of their operation in the human-shared environment (Clothier and Walker, 2006). Despite many possible applications of the small-scale UAVs, such as civil security control, traffic supervision or environmental management, a reliable safety mechanisms are essential for their ubiquitous operations (Mohammed et al., 2014). A possible solution is an introduction of the fault-tolerant control (*FTC*) techniques that increase the reliability of the micro UAVs by ensuring some minimal degree of system's performance during fault scenarios (Valavanis, 2017). Recently, a problem of designing and developing active FTC systems becomes particularly popular for certain aerospace applications (Fekih, 2014). While passive fault-tolerant control relies mainly on methods that are robust enough to withstand system faults, an active approach consists of the *Fault Detection* (FD, FDI) module, a system's component that detects, identifies and localizes the fault. On this basis, the re-arrangement of control strategy is introduced (Witczak and Pazera, 2016), (Fekih, 2014). The active approach to the *FTC* is the main principle of the solution presented in this article. There are two most common types of possible system faults in multirotor UAVs: errors in the state estimation methods caused by the faulty or inaccurate sensory system (Gardecki et al., 2014) and impairment of the actuators. Propulsion faults include an improper operation of electric motors, faulty electronic speed controllers (*ESCs*) and above others, physical impairment of rotor blades (Gorospe and Kulkarni, 2017). This last type of system degradation is exceptionally dangerous because it leads to the loss of the thrust force, disturbed thrust balance and increased power consumption. Moreover, increased airframe vibrations degrade quality of the state estimation as well (Qi et al., 2013). As most of multirotor UAVs are underactuated systems, the loss of a single motor-propeller unit may easily lead to a crash (Valavanis, 2017). In addition, propeller blade damages are very likely to occur in real-world scenarios, especially during the flight in closed spaces.

In this paper, a data-driven method for detecting and isolating rotor impairments in the micro multirotor UAV system is presented. An algorithm is based on the analysis of vibrations signals obtained by the network of sensors located in a few designated places of the mechanical structure of the UAV. Information about fault occurrence and its location is extracted from the set of signal features with the following classification stage. This paper is organized as follows: next section mentions related research and solutions. The third part presents the problem statement and ini-

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tial assumptions made prior to the development of the presented method. Sections 4-6 present in details the principles of operation of the fault diagnosis system, both in terms of hardware structure and software algorithms. The seventh section describes the experimental setup and shows the results and performance of fault diagnosis evaluated during the series of test flights. A final chapter summarizes the whole article and points some drawbacks of the method as well as possible future endeavors.

2 RELATED WORK

Fault detection methods for multirotor UAVs fall into two general schemes of *FD* systems: model-based and model-free approaches (Fekih, 2014). The first category of solutions require precise, parametric model of the aerial vehicle and utilize different kinds of state observers and Kalman filtering techniques to detect a variety of possible faults (Merheb et al., 2014), (Zhaohui and Noura, 2013) and (Rago et al., 1998). On the other hand, another class of methods utilizes expert knowledge and machine learning in the model-free approaches (Fekih, 2014). In some cases, characteristic features and indicators of faulty system states are obtained thanks to the signal processing algorithms.

A vibration-based condition monitoring is a well-known technique, especially when it comes to the fault diagnosis in the machinery consisting of the rotating parts (Nandi et al., 2005). However, there are only a few attempts to use a signal-processing based methods for the fault detection in the field of multirotor UAVs (Jiang et al., 2015). A prior research performed by authors resulted in a simple, signal-processing based fault diagnosis solution based entirely on the data acquired by the on-board *AHRS* (*Altitude and Heading Reference*) subsystem (Bondyra et al., 2017). However, this method was unable to localize faults, only to detect their occurrence and estimate their scale.

3 PERFORMANCE OF THE PROPULSION SYSTEM WITH IMPAIRED ROTORS

Prior to the development of the fault detection method, authors tried to estimate the impact of rotor blade damage to the performance of multirotor UAV propulsion system. A series of stationary thrust tests were performed using the custom-built test stand

Figure 1: The propulsion test stand and set of tested rotors with different degrees of structural damage.

(Aszkowski et al., 2017). During the experiment, a set of three typical 10-inch propellers was used. A complete propulsion unit consisted of propeller, Electronic Speed Regulator (*ESC*) and *MN3310* BLDC electric motor. While the first blade set was in a brand-new condition, two other propellers were subjects to different degrees of damage.

Measured parameters were thrust, angular velocity of propellers and power consumption in relation to the whole range of the *PWM* control signal. Results of performed tests are illustrated in the Fig. 2.

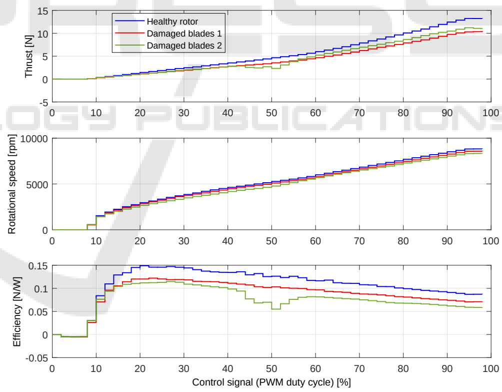

Figure 2: Propulsion performance measurements with healthy and damaged rotors.

Analysis of the operation of impaired rotors leads to a couple of conclusions. While the *ESC* ensures that the angular velocity of propellers remains unchanged, the loss of generated thrust can be observed even in the case of a slight blade damage. The power efficiency of the propulsion unit, defined as a thrust generated with a single watt of electric power, decreases significantly. In addition, a major disturbance in thrust measurements can be observed in the middle of the control signal range. Analysis of the remaining data recorded by the 6-axis force/torque sensor lead to the conclusion that mechanical resonance is caused by the increased level of vibrations generated with the rotating propeller. This observation suggests that even slightly damaged rotors cause a significant and observable increase of structure vibrations, which can be analyzed and processed in order to identify and locate the fault.

4 SENSOR NETWORK ARCHITECTURE

The approach presented in this article is based on the development of a specialized embedded system that serves as a real-time diagnostic module for an arbitrary multirotor UAV. Aims of the design were to provide a low-cost and versatile system, independent from the applied flight controller. Three different categories of components were used:

- **Sensory modules**, designed as miniature printed circuit boards equipped with the *MMA8452* low cost, 3-axis accelerometers along with a few auxiliary components. Every single module is placed close to the consecutive propulsion unit (the *ESC*-motor-rotor set). The sensors' reference frames are set in an identical manner in relation to the work plane of the closest rotor. The PCBs are mounted in the 3D-printed plastic brackets to ensure proper propagation of vibrations from faulty propellers to acceleration sensors. For the purpose of this research, a set of four sensors was used along with quadrotor UAV. However, the number of sensors can be easily extended to fit hexa- and octo- copters, as long as there is one sensor for every propulsion unit. Parameters and configuration settings of the MEMS sensors used in the project are presented in the table 1. In the description below, g denotes the earth's gravitational acceleration.

Table 1: Operational parameters of the MMA8452 accelerometer.

Parameter	Value
No of sensing axes	3 (cartesian)
Data rate	400Hz
Sensing range	+-8g
Digital resolution	12-bit
Measurement resolution	3.9mg
Unit cost	2 EUR

- **Data acquisition unit** (*DAQ*), developed as a single PCB equipped with a *STM32F4*-family microcontroller. The module is located in the central part of the UAV and delivers a supply voltage for the rest of *FDI* system components. Sensor modules are connected using the high-speed I^2C bus with a serial bus clock set to 400kHz. The microcontroller's firmware polls periodically the set of sensors and converts raw measurements into readable data frames. Each data packet contains vectors with measurements of axial and radial vibrations for every accelerometer and corresponding propulsion unit. The data is collected with the rate of 400Hz, which corresponds to the output data rate of *MMA8452* sensors.
- **Data processing unit**, used for the final data acquisition, storage and processing. Authors utilized an easily available *Raspberry Pi Zero* miniature, single-board computer. However, any advanced processing platform may be used, as long as its weight meets the lift capabilities of the UAV. The computer is running a Linux operating system and acquires data packets from the *DAQ* via the serial interface.

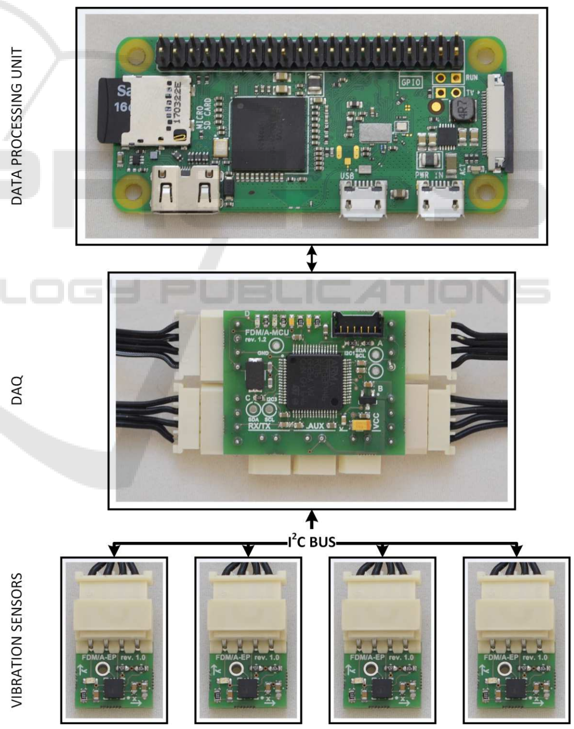

Figure 3: Hardware architecture of the developed FDI system.

5 ANALYSIS OF VIBRATION SIGNALS

Authors assumed that the main frequency of vibration signal will correspond to the angular velocity of the damaged propeller. Therefore, the initial signal analysis focused on observing vibration spectra obtained by the network of sensors. First experiments were performed during steady hover flight, with the angular velocity of rotors as constant as possible. A *Falcon V5* drone (Bondyra et al., 2015) was selected for the test platform along with the embedded system described in the previous section. Fig. 4 presents the UAV partial CAD model along with sensors placement and propulsion units' notation.

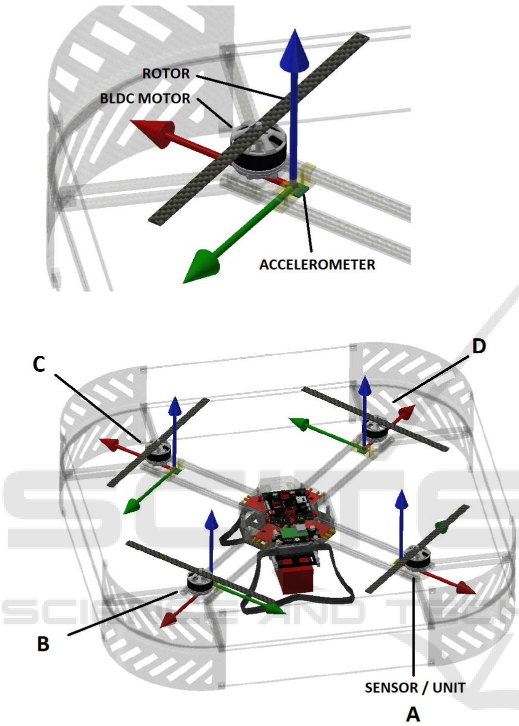

Figure 4: The partial CAD model of the Falcon V5 UAV with locations of vibration sensors.

The aim of this approach was to determine some dependencies in the vibration signals which could be used for the fault classification algorithm. Fig. 5 shows exemplary averaged spectra of radial and axial vibrations obtained during 10 seconds of the data acquisition. In this case, all four rotors were undamaged.

Overview of recorded spectra shows a significant amount of vibrations of the mechanical structure of the UAV. However, no indicator of actuator faults can be seen. In another scenario, the fault occurred at the propulsion unit **A** with the angular velocity of propellers varying between 550-600 rad/s. Spectra of recorded vibration signals are shown in the Fig. 6.

Measurements of radial vibrations show clearly the faulty state with the characteristic vibration frequency of about 90 Hz. However, the spectral peak

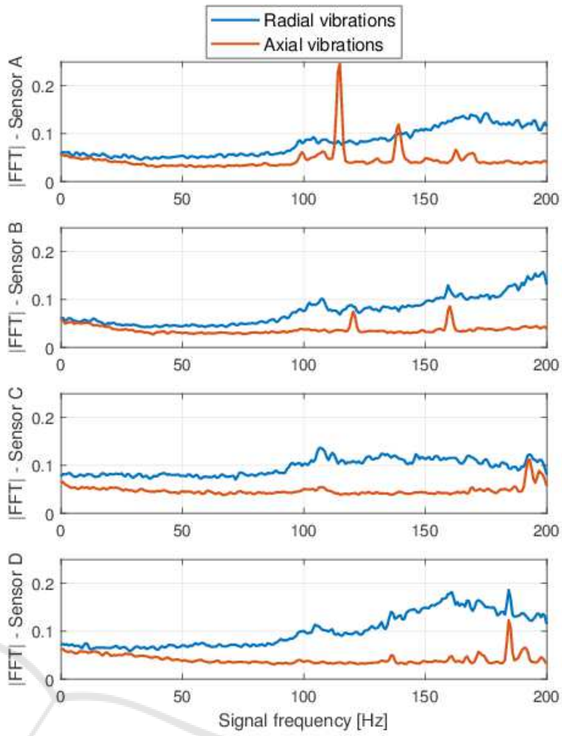

Figure 5: Averaged spectra of vibration signals recorded with undamaged rotors.

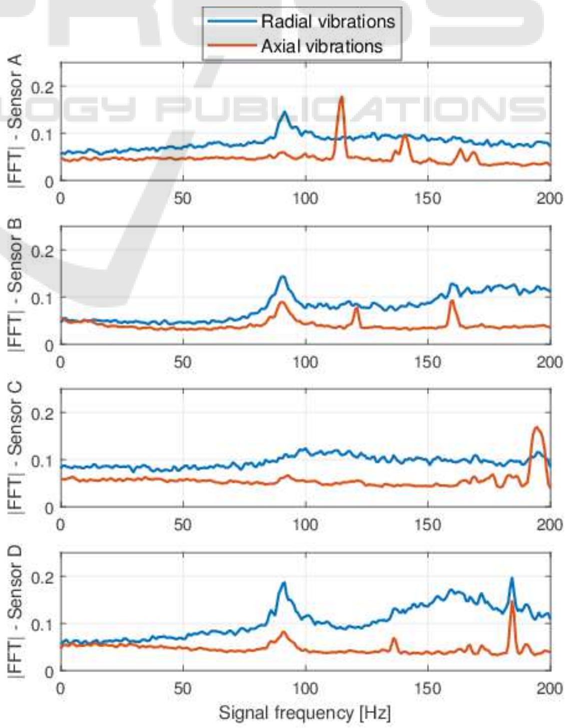

Figure 6: Averaged spectra of vibration signals recorded during the fault occurrence at the unit A.

can be observed with the highest amplitude at the sensors **B** and **D**. The spectrum obtained with the sensor placed closest to the faulty actuator (**A**) shows moderate frequency peak, while the sensor **C**, located at the opposite end of the UAV mechanical structure indicates the dampening of the fault frequency. These observations lead to the following conclusions: due to the nature of the vibration propagation along the airframe of the multirotor, the fault indicators are not necessarily shown by the closest accelerometer. Observations from all of the sensors are required to determine fault location. However, the spectral patterns are clearly visible for the fault detection itself. On the other hand, characteristic fault frequency varies during the flight with regard to the angular velocity of rotors. In addition, a variety of frequency components from different vibration sources can be seen in spectra. It leads to a conclusion, that simple fault frequency detection methods are insufficient and a machine learning mechanism can be introduced.

6 FAULT DETECTION METHOD

An algorithm for the fault detection and localization comprises three main stages:

6.1 Data Acquisition

The vibration signals are acquired thanks to the set of *MEMS* sensory modules and the *DAQ*. Then, some basic operations are performed on the raw signal vectors: the normalization and windowing of the samples using the Hanning window. The length of the sampling window (T_w) is a parameter affecting the performance of the diagnostic method. Its impact is presented in the section 7.

6.2 Feature Extraction

For pre-processed signal vectors, the single-sided amplitude spectrum is computed using the Fast Fourier Transform (*FFT*). Then, for 16 predefined frequency ranges (frequency bins), the RMS of the spectrum is computed. Calculated values create a vector of features for single-axis, single-sensor measurements. Frequency bins are linearly spaced and have an equal width of 5Hz. However, lower and upper frequency limits for the first and last bin are parameters to be tuned. Since the fault frequency corresponds directly to the angular velocity of UAV rotors, the spectrum analysis window is narrowed to fit between 60 to 140 Hz. These frequencies resemble angular velocities within the range of 370 to 880 rad/s, which are typical for most propulsion systems of micro multirotor UAVs. The process of splitting the amplitude spectrum into frequency bins is summarized graphically in the Fig. 7.

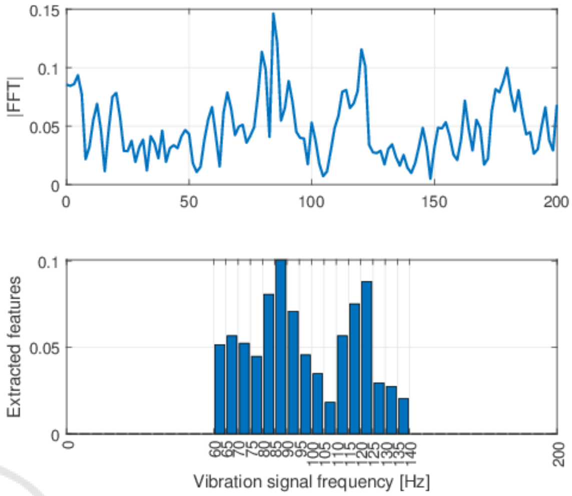

Figure 7: Principles of the feature extraction: single axis vibration spectrum with corresponding set of calculated signal features.

With features extracted from the axial and radial measurements of every accelerometer, the feature vector is formed. The data measured at the vertical axis was omitted because further analysis has shown the negligible significance of obtained features. A complete vector of vibration features for quadrotor consists of 128 elements with axial and radial features of four propulsion units.

6.3 Fault Signature Classification

The final stage of signal processing pipeline is a feature classification. A set of random decision trees (Breiman, 2001) was used for this task. In order to detect and isolate actuator faults, a classifier processes computed vector of features and assigns an adequate class based on the trained vibration patterns. Its principle of operation is based on aggregating many weak classifier grouped in common ensemble (*bag*). A random subset of predictors is chosen for each decision split during the process of growing decision trees. The classification is based on the majority vote between final outcomes.

The classifier adjusted for quad-rotor UAV is trained to recognize 11 different classes: all-healthy rotors state, single faults in each propulsion unit and double simultaneous impairments for every possible pair of rotors.

During the experimental stage (see sec. 7), a wide dataset was acquired, with more than 13000 independent data samples. The acquired data was split randomly into 70 % of training dataset while remaining 30% was used for a validation. A summary of the fault detection and isolation process is presented in the Fig. 8.

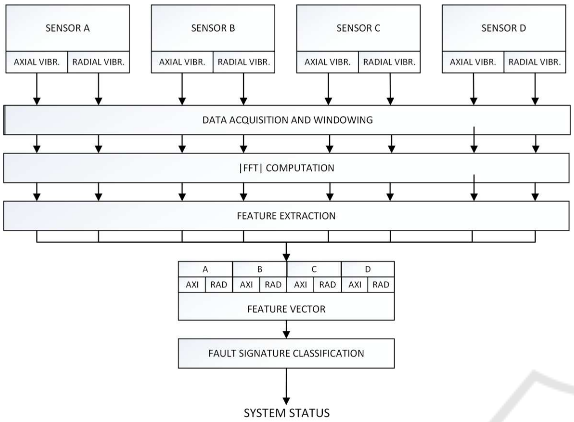

Figure 8: Data flow diagram of the fault detection and isolation system.

7 PERFORMANCE EVALUATION

7.1 Experimental Setup

In order to gather the dataset and validate the performance of developed fault detection and isolation system, a series of test flights was performed. The *Falcon V5* drone in the quad-rotor configuration was used for this task. During experiments, a variety of possible actuator faults were tested. First few flights were executed with all rotors in a brand-new condition. Other tests were performed with damaged propellers: all cases of single unit faults and some double rotor impairments, with adjacent and opposite pairs of damaged rotors. For every case, over 300 seconds of the in-flight vibration data were recorded while the UAV performed different flight maneuvers. Then, the acquired dataset was post-processed in order to train the classifier and validate the method. A complete FDI system, consisting of vibration sensors, *DAQ* and data processing unit was mounted on-board of the UAV. Fig. 9 shows the *Falcon V5* UAV during the flight.

7.2 Tuning the Classifier

The processing of the experimental results has shown that two parameters are essential to determine the performance of detecting the fault occurrence and localization.

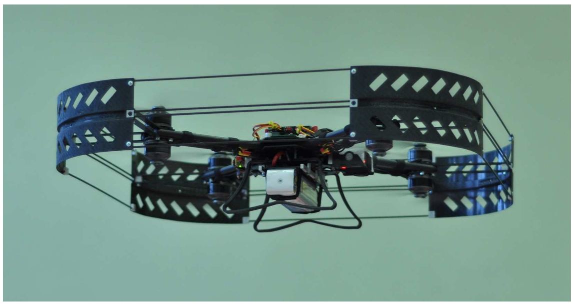

Figure 9: Falcon V5 UAV used for the performance evaluation of the FDI system.

Since the time of the acquisition of axial and radial vibration signals is variable, the longer is the time window, the more information and higher significance of signal features can be obtained. In addition, an increased number of decision trees in the ensemble may provide a higher accuracy. An analysis was performed on the basis of an *out-of-bag* (OOB) error estimate chosen as a parameter to determine the accuracy of the classification. The *OOB* measure delivers the estimate of true classification errors based on testing the examples excluded during the training stage(Banfield et al., 2007). The dataset obtained during the series of test flights was evaluated in relation to the window length and number of decision trees. Results of the experiment are shown in the Fig. 10.

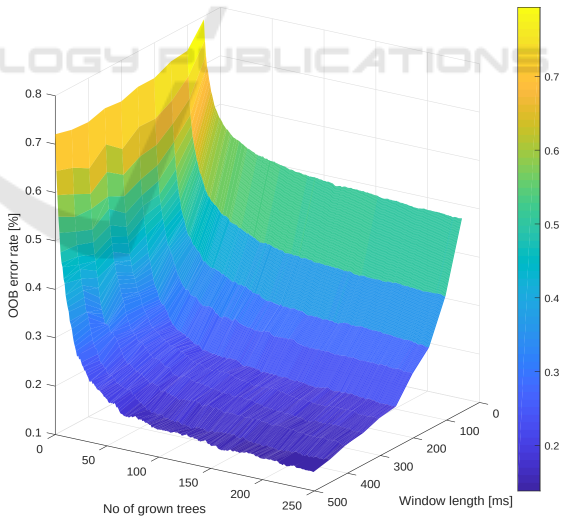

Figure 10: Performance evaluation of the classifier.

An initial performance evaluation lead to a conclusion, that vibration signals have to be acquired for at least 0.2 seconds ($T_W = 200ms$). This time period is the most significant factor influencing the fault detection time lasting since the occurrence of the impairment to the final decision of the *FDI* system. A number of decision trees required for the correct classification of fault signatures has a lesser impact since bags of several hundreds trees are not computationally demanding.

7.3 Experimental Results

After initial tuning of the classifier parameters, a window length of 300ms was chosen for the exemplary performance evaluation. The complete ensemble of random decision trees consisted of 200 instances. The fault detection and isolation system was validated with remaining 30 % of the dataset.

Ground truth: FAULT LOCATION \ Classifier output: FAULT LOCATION	-	A	B	C	D	AC	CD
-	99,18	0,00	0,00	0,82	0,00	0,00	0,00
A	0,89	97,32	0,89	0,89	0,00	0,00	0,00
B	0,00	0,00	93,91	0,00	2,61	3,48	0,00
C	0,89	0,89	0,00	98,21	0,00	0,00	0,00
D	0,00	0,00	1,52	2,27	93,94	2,27	0,00
AC	0,88	3,54	10,62	0,00	5,31	65,49	14,16
CD	0,00	2,20	4,40	0,00	0,00	45,05	48,35

Figure 11: Results of the fault detection and isolation experiment - confusion matrix for $T_W = 300ms$ and the ensemble of 200 decision trees.

According to the Fig. 11, the *FDI* system has proven very high accuracy in detecting the fault occurrence itself. In over 99% of cases, a healthy state of rotors was properly identified. In addition, single rotor impairments were detected correctly in over 93.9% of cases. However, faults in units **A** and **C** are recognized in more cases. It may lead to a conclusion that the proper placement of the sensors may affect the performance of the fault detection since every vibration sensor is mounted in the same relation and distance to the propulsion unit. Double rotor damages are harder to detect, but they are rarely mistaken for the healthy state. In most cases of the wrong classification, the localization of damaged units failed, while the system indicated correctly that the dual fault occurred. Especially the detection of two faulty adjacent actuators (the **C-D** pair) was harder to distinguish from other fault classes.

7.4 Comparison of Results

Very few methods based on the signal processing of airframe vibrations can be found in the literature. However, the performance of fault estimation method was compared with some similar algorithms. Sensitivity of presented method exceeds 95%, which is similar to existing solutions (Jiang et al., 2015), (Bondyra et al., 2017). Another performance factors, such as rate of missed faults and false detection of occurrence are comparable as well. However, these methods lack the ability to isolate the fault and deliver its precise location, which is the main advantage and novelty of presented approach.

8 CONCLUSIONS

Several advantages of the proposed solution can be pointed out. The developed fault detection and isolation system provides high detection rate. Fault occurrence is detected in more than 95 % of cases using quite a simple signal processing methods and not computationally demanding classification method. In case of single actuator faults, implementation of the network of vibration sensors allows to isolate and localize fault precisely. Clear indicators of double rotor damages are provided. However, these categories of faults are easily mistaken in terms of isolating the specific faulty rotor pair. In addition, utilizing an external, signal processing based system is a very versatile solution and can be easily implemented in the arbitrary multirotor UAV with the small cost.

On the other hand, in case of implementing the external sensor network, additional equipment of the UAV is required. Moreover, the response time of the *FDI* system is dependent mostly on the time of signal acquisition. Hence, there is some significant delay between fault occurrence and diagnostics information. Application of the presented *FDI* system to the arbitrary multirotor requires a process of training of the classifier. Further research will focus on tuning the method, decreasing the required data acquisition time and implementation of the fault detection system with the corresponding fault-tolerant control scheme.

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