Survey of fault diagnosis and accommodation of unmanned underwater vehicles

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Abstract

In the last years, the use of unmanned underwater vehicles in various applications such as monitoring, inspection and surveillance of underwater facilities, has been significantly increased. The mission success depends heavily on the ability to diagnose, isolate and accommodate faults that may occur in the thrusters and sensors of the vehicles during the operation. This paper presents an overview on the methods employed for thruster and sensor fault detection, isolation and accommodation of underwater robotic vehicles.

1 Introduction

Over the last decades, there has been a significant increase in the use of Unmanned Underwater Vehicles (UUVs) in missions such as exploration of the oceans, inspection of underwater structures or pipelines, monitoring of underwater environmental changes, exploration of the sea bottom etc. The UUVs can be divided into two categories, namely, the Remotely Operated Vehicles (ROVs) and the Autonomous Underwater Vehicles (AUVs). The operation of an ROV is more limited in comparison to an AUV, because it must be controlled by qualified personnel and it is tethered to a control cable. On the other hand, AUVs have the ability to operate autonomously, in terms of energy and computational resources. However, the concept of autonomy for both categories of underwater vehicles is limited by the occurrence of faults.

Faults can be identified into two categories: a) the ones that can be restored and b) those that cannot be restored. A fault can be addressed either by adapting the motion or behavior of the underwater vehicle via an appropriate recovery algorithm or by exploiting potential redundancy in sensors or actuators. In any case, the vehicle will be able to continue its trajectory and perform the scheduled mission, even with reduced capabilities. A fault that cannot be restored is characterized by the complete damage of a control or motion component or to a partial loss of its functionality, which ultimately leads to failure in performing the mission. In this case, the vehicle must be retrieved to the surface for repair and maintenance.

The faults typically appear on either the thrusters or the on-board sensors of the vehicle. Thrusters are responsible for moving and accelerating the underwater vehicle in 3D space. Therefore, when a thruster fault occurs, the actuation capabilities of the vehicle are reduced. In that case, if redundancy of thrusters exists then the vehicle may continue its trajectory with the same or reduced performance (thruster fault tolerant control). However, if there is no excess of thrusters or faults occur in multiple thrusters at the same time, the fault is considered critical and the mission is aborted. Additionally, the reliable functionality of the on-board sensors is of utmost importance. Through the feedback provided by the sensors the closed loop motion control of the vehicle is achieved. Hence, a possible damage to the sensor suite may severely affect the overall performance of the vehicle. Also, increased measurement noise in the sensor signal, can be considered as fault, which must be dealt in order the underwater vehicle to continue its mission smoothly.

According to the aforementioned discussion it is easy to perceive the crucial role of fault diagnosis in the proper operation of an underwater vehicle. In [1] the author presents two techniques that can be used for fault detection and isolation (FDI), one complementing the other. The first technique is called model based or analytical and relays on the use of mathematical models and algorithmic methods to describe the behavior of the system to be studied. The second is called no model or knowledge based and relays on the performance of multiple tests, as well as the collection of large amount of empirical data (redundancy). According to [1], the analytical methods employ quantitative models, while the empirical methods use quality models based on the available knowledge of the system. In conclusion, the combination of these two methods may deliver the best results for fault diagnosis.

The rest of the paper is organized as follows: Section 2 presents methods for fault diagnosis on thrusters, while Section 3 is devoted on sensors fault diagnosis. Finally, Section 4 concludes the paper.

2 Thruster fault diagnosis methods

As previously discussed, thruster faults may compromise the reliable operation of the underwater vehicle. Thus, it necessary to detect and isolate the fault as soon as it appears. On this topic several methods have been published which are presented below.

2.1 Thruster fault diagnosis

According to [2], the solution to the problem of thruster fault diagnosis involves residual generation based on the inconsistency between the actual behavior of the vehicle and the behavior of the reference model. The decision that will be taken to diagnose the fault will result from the assessment of the residuals. To address a fault there are two solutions, the active and the passive one. The active solution is based on a new control law applied to each case of fault, either by addressing the fault within the existing structure of the system or by leading to a reconfiguration of the system. The passive solution is based on the probability of applying the control law to manage the fault. The authors in [2] propose the first solution.

A similar technique is used in [3], where it is mentioned that the fault detection and diagnosis is achieved by assessing any significant change in underwater vehicle's behavior. This work is carried out by a bank of estimators. In particular, an Extended Kalman Filter (EKF) has been applied to each type of thruster fault, including the no-fault case. The EKF was selected in order to handle the presence of non-linearity in the dynamic system.

In order to solve the problem of detecting and identifying simultaneous faults in AUV thrusters and sensors, the authors in [4] propose a quantitative/qualitative hybrid diagnostic method combining neural networks with dynamic trend analysis. The authors in [5], apply a slightly different method based on a mathematical model that uses a Gaussian particle filter to identify a fault in the propellers.

In [6] in order to identify and isolate thruster faults in an AUV, the authors designed a discrete time diagnostic observer. A Support Vector Machine (SVM) architecture was employed in order to process off line the data collected during tests where there was no error. Finally, the residuals were calculated based on the observer's outputs and the measurements from the system state. To detect and estimate the unknown thruster fault, a Radial Basis Function (RBF) network built into the observer was employed.

A different technique for detecting thruster faults is presented in [7]. This approach proposes the implementation of a research policy learned from a simulated underwater vehicle model. The model adapts to a new condition when a fault is detected and isolated. This approach can create an optimal trajectory and navigate the AUV to a set target at minimal cost, even when the AUV is not working properly due to the presence of a fault.

All the previous researches for the diagnosis of thruster faults were referred to unmanned underwater vehicles. In contrast, in [8] and [9] the presented approaches refer to ROVs. The main effort in [8] was to develop a model for fault detection and isolation at various levels of architectural control, such as servo-amplifiers, dynamic model-based design and steady state monitoring. The aim is to develop a reliable diagnostics system based on information redundancy.

In [9] the proposed fault detection system performs fault diagnosis on ROV thrusters by using measurements for the vehicle (surge, sway, yaw) motion as well as for the corresponding speeds, without relying on actuator measurements. The detection system consists of a residual generator and an evaluation module. The residuals generator is based on a nonlinear observer (Thau nonlinear observer). The residual evaluation was done with a sequential change detection algorithm.

The authors in [10] proposed a geometric approach to the issue of completely unblocking the residuals of the faults. Most methods used to diagnose faults in nonlinear systems are based on residual generation and require a structural analysis. The proposed geometric approach is based on the assumption that faults do not occur at the same time, and sufficient conditions are created for the faults isolation in nonlinear systems.

2.2 Thruster fault accommodation

In [11] the authors present a Fault Diagnosis and Accommodation System (FDAS) which includes two subsystems: Fault Diagnosis System (FDS) and Fault Accommodation System (FAS). The FDS is a hybrid, on-line, model-free approach, based on integration of a Self Organizing Map (SOM) and fuzzy clustering methods. In the training phase, the FDS uses data obtained during test trials to find SOM representatives for each fault type. In the detection phase, the FDS makes decision about fault type by comparing the position of feature vector relative to these maps. The results demonstrate efficiency and robustness of the FDS. The FAS uses the output of the FDS to accommodate faults and perform reconfiguration by updating weights used in the optimization criteria and thruster velocity saturation bounds.

Another method developed to accommodate thruster faults is proposed in [12], which is based on thruster redundancy. This approach is then extended to incorporate a dynamic feedback technique for generating reference push forces within the saturation limit of each thruster. This redundancy can be utilized to achieve additional power for the AUV and to enhance the vehicle's ability to fulfill its mission objectives in the event of a thruster fault.

2.3 Thruster fault tolerance

Assessing all the above, we conclude that thruster faults can be crucial for the performance of the underwater vehicle and the mission success. In [13] the authors report that tackling a thruster fault can be dealt with inherent redundancy of thrusters. Indeed, tolerance to actuator faults is a key issue in underwater robotics, since a thruster failure can prove critical in task completion.

According to [14], the thruster fault can be treated as an uncertainty added to the dynamic model, similar to the uncertainties of system modeling (external disturbances from the marine environment). The sliding mode algorithm is an effective means of controlling a non-linear system (such as an underwater vehicle), due to its strong ability to compensate system uncertainties and external disturbances. Sliding mode control is widely used in non-linear systems with great uncertainties.

The authors in [15], refer to the separation of AUVs where two categories in terms of motion capabilities can be identified. In the first class, the motion is continuous and resembles to the one of airplanes. These are called cruising AUVs and they are characterized by less number of thrusters comparatively to the available degrees of freedom. In the other category, AUVs with the ability to move in all directions, as well as to stabilize in one point appear. The latter property is of utmost importance in observation missions. These are called hovering AUVs and the number of their thrusters is greater than the available degrees of freedom. Thruster redundancy is a key property in fault tolerance control. In the same work, experimental results from tests performed using an AUV with four horizontal thrusters and two vertical ones are presented. The goal of the experimental procedure was to determine whether the AUV can follow the prescribed trajectory with a fault: (i) to a horizontal thruster, (ii) to two horizontal thrusters and (iii) a vertical thruster. In cases (ii) and (iii) the number of active thrusters is less than the number of degrees of freedom. Tests have shown that the AUV can follow the programmed trajectory on a horizontal plane while maintaining the desired depth using only three thrusters, where two are horizontal ones. However, in some cases changes had to be made to the preferred direction of the AUV motion.

In [16] the authors present a fault diagnosis system consisting of two units. One performs a fault diagnosis and the other fault accommodation. The fault diagnosis module is based on a neural network fusion information model to detect the thruster fault. The fault accommodation unit is based on direct motion calculations and the fault identification results are used to find a solution to the control allocation problem. The proposed method attempts to diagnose and accommodate the subsequent faults detected during the mission.

Another attempt to create an integrated fault tolerant control system (AFTC), which can perform detection, diagnosis and fault accommodation, is the one proposed in [17]. The system includes an integrated fault detection and isolation (FDI) technique based on: (1) a model based FDI that uses a bank of Kalman filters, (2) an algorithm for estimating the efficiency factor of the faulty sensor or the faulty thruster, (3) an approach to redesign the on-line controller in order to compensate the detected fault before the system leads to a degradation of its performance or to complete destruction.

3 Sensor fault diagnosis methods

As previously mentioned, sensors faults are equally important for the proper functioning of an underwater vehicle. To diagnose these faults, several attempts have been made and various approaches have been proposed.

In [18], the authors identify that one of the problems in sensor fault diagnosis for AUVs, is the added mass when the vehicle performs maneuvers, which should be represented as an unknown time-varying parameter of the model. To accommodate this problem, a method based on a model based approach using AQLPR (adaptive quasi-linear parity relations) is proposed. This method combines the advantages of the closed loop and the open loop techniques. The characteristics of this method are: (i) adaptability to unknown added mass in the diagnosis process including closed loop techniques (ii) decoupling from the slowly changing added mass at the diagnostic stage including open loop techniques.

In [19], two methods for sensor fault diagnosis are presented. The first is the analytical redundancy (AR) method, while the second is the multivariable statistical based data method. The first method works well when there is an available and clear process model. However, such model cannot be easily achieved due to the non-linear dynamics and high complexity of many systems. A more widespread statistical method, Principal Component Analysis (PCA), employs a clear model of the system that uses data obtained during the no-fault operation of the system. According to this method, faults are detected by comparing the actual outputs with those predicted by the model. However, PCA is a linear method and cannot be applied to non-linear systems such as AUVs. For this reason, a nonlinear version of PCA, KPCA (Kernel PCA), which can be applied to nonlinear systems, is also used. Particularly KPCA (Partial KPCA, PKPCA) can also be applied for fault detection and fault isolation. For best results, the authors suggest applying KPCA for sensor faults and PCA for thruster faults.

The work presented in [20] refers to faults in the Doppler Velocity Log (DVL) sensor. The faults frequently appear in this class of sensors, are of two kinds: (i) the sensor output remains unchanged and (ii) the output jumps at a time or over a period of time. To accommodate the problem, a method based on strong tracking filter (STF) theory and a singer model of the first order time correlation function is proposed. The proposed method was used for velocity output identification and velocity sensor fault diagnosis.

In [21], a new method is proposed that combines phase space reconstruction and an extreme learning machine. This method is applied to predict the output of the sensor and achieve fault diagnosis. Specifically, data is initially collected from the normal fault-free sensor's operation and an ELM model (Extreme Learning Machine) is constructed. The residuals are then calculated on the basis of predictive outputs and measurements of the state of the system. The model outputs will be used when there is a problem with the sensor, in order to compensate for the actual, but false outputs that the sensor will deliver. Finally, when a sensor fault occurs, the outputs of the ELM model can be used instead of the actual sensor outputs to compensate for the sensor failure. In recent years, ELM has been significantly increased to solve sensor problems described by nonlinear models. This is due to the fact that ELM can learn much faster and with higher generalization performance than traditional learning algorithms. It is also capable of solving problems related to precision, calculation costs, and local minimum.

In [22], the authors propose a second order dynamic prediction gray algorithm GM(2.1) for the fault detection in a fiber optic gyro sensor. The GM(2.1) is a modeling method based on a gray generation function and with a differential fitted to the core. It is based on a small number of known information to predict the next data acquisition from the sensor. If the predicted data do not match the received data from the sensor, then a fault is recognized, and the resulting data is sent to the system. The strong point of this method is the short fault recognition time.

In [23], a system based on diagnostic observers and data fusion of signals from sensors using a Kalman filter was suggested. The error-free data from the observers is compared with the actual data sent by the sensors. The residuals that may be produced from this comparison indicate the occurrence of a fault, but an estimate of the size of the fault is also made. The estimates of the measured values, which are used to generate the control signals, are then calculated. This system combines the kinematic model of the vehicle with the data acquired from the sensors and allows the fault detection and accommodation for the sensors of an underwater vehicle.

Conclusion

This paper presents a bibliographic survey of the methods appear in fault diagnosis and accommodation for thrusters and sensors of underwater robotic vehicles. There are several approaches that are of particular scientific interest and with proven results that approximate the original purpose of fault diagnosis. Nevertheless, existing works regarding the fault accommodation in thrusters and sensors of underwater vehicles are still limited.

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