

Introduction

In fault identification and risk management (FIRM) project, SDSMT and NUWC Keyport are developing a new method to online diagnosis and management of faults in UUV sensors and actuators. Faults in the system do not have any specific and predictable pattern and therefore, detection of faults need an accurate detection strategy. The proposed FDI technique is a neural network (NN) based detection design in which its learning weight are updated online through the EKF algorithm.

AUV Nonlinear Dynamics

The 6 DOF nonlinear model of the AUV is described as follows (Fossen 2002):

$$\dot{\eta} = J(\nu)$$

$$M \dot{\nu} + C(\nu)\nu + D(\nu) + g(\eta) = \tau$$

M includes rigid body mass and added mass matrices, $C(\nu)$ includes coriolis and centripetal matrices, $D(\nu)$ includes quadratic and linear drag matrices, $g(\eta)$ includes gravitational and buoyancy matrices and τ is the force and torque vector.

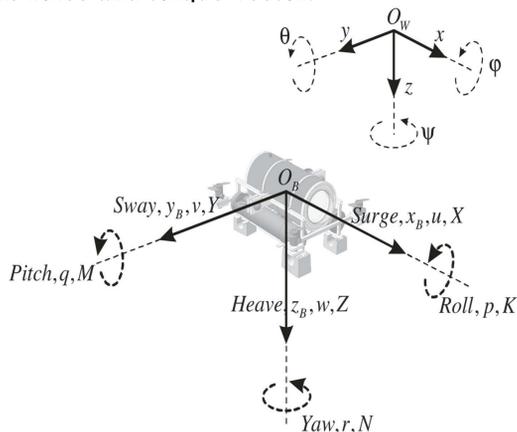


Fig 1: Definition of the reference AUV frames

NNAS

Faults in a system may be nonlinear and unpredictable; hence, artificial neural network (ANN) can be a suitable candidate for their estimation. The proposed Fault Detection and Isolation (FDI) technique is a neural network (NN) based detection design in which its learning weight are updated online through EKF. Unlike the direct ANN modeling procedures that use an ANN to simulate the system behavior, the proposed NN Adaptive Structure detects faults based on the output of the nonlinear observer:

$$\dot{\hat{x}} = f(\hat{x}(t)) + g(\hat{x}(t))u(t) + f_a(t)$$

$$\hat{y} = h(\hat{x}(t))$$

where \hat{x} is the state vector of the nonlinear observer and $f_a(t)$ is the NNAS detection signal that is the observer that is defined as:

Fault Detection and Isolation (FDI)

The input of the observer $f_{ai}(t)$ is the i^{th} vector of $f_a(t)$ defined as:

$$f_{a_i}(t) = W_i(t) \sigma(V_i(t) \delta_i(t))$$

$f_a(t)$ recursively updated with the previous m , and also previous n samples of the system output error $e_i(t) = y_i(t) - \hat{y}_i(t)$.

$$\delta_i(t) = [f_{a_i}(t-\tau), \dots, f_{a_i}(t-m\tau), e_i(t-\tau), \dots, e_i(t-n\tau)]^T$$

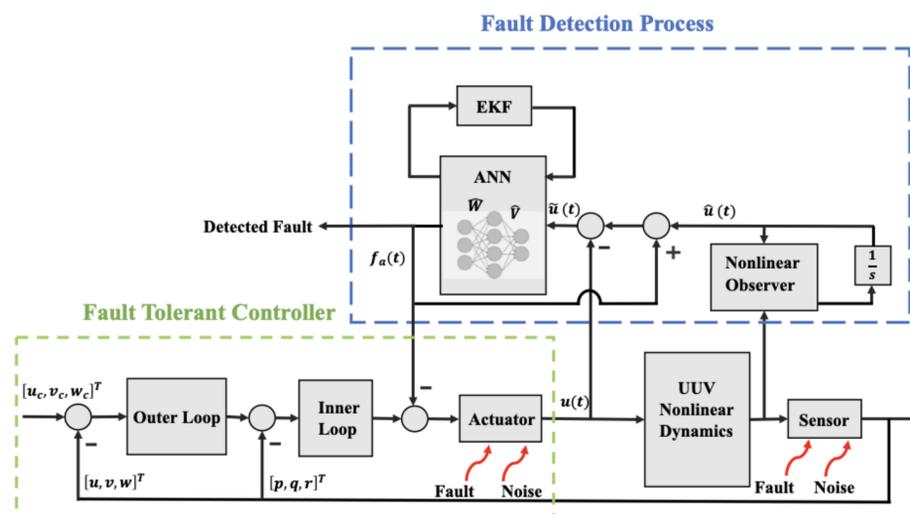


Fig 2: Proposed FIRM framework for fault detection and compensation for UUV.

Fault Tolerant Control (FTC)

In order to achieve real-time performance, the NN weights should be tuned effectively. In this study, an adaptive tuning algorithm based on EKF is introduced. The EKF helps to update the NN weight in parameters online, so that fast convergence rate of the NN learning will be guaranteed.

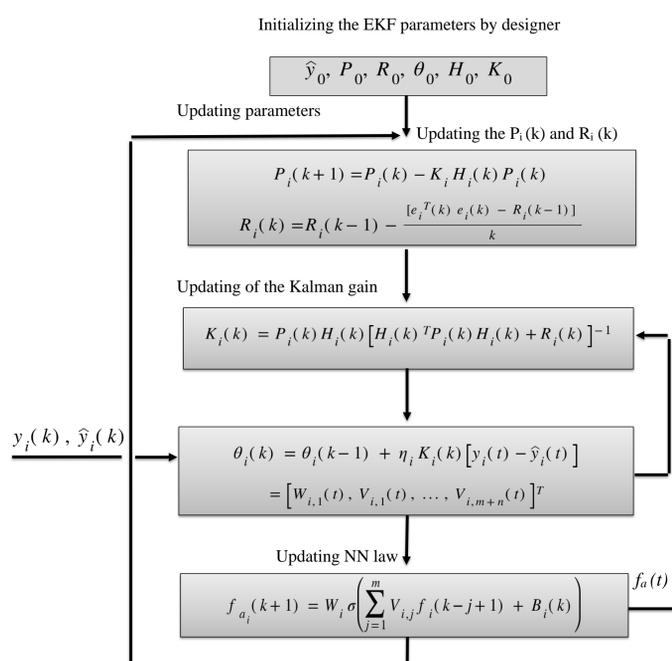


Fig 3: Block diagram of the Neural Network Adaptive structure (NNAS)

The NNAS active FTC design, consists of two parts:

- 1) The *Nonlinear Dynamic Inversion Controller* (NDI) control
- 2) The *Adaptive Fault Compensation Feedback Controller*.

Fig. 4 shows prior work where a triangular fault is applied to the aileron of UAV, it shows the injected (solid line) and detected (dashed line) fault in the aileron actuator. Fig.5 show that the NNAS-based FTC design for UAV and its ability to compensate for the fault effects based on the detected fault by FDI.

Preliminary Results

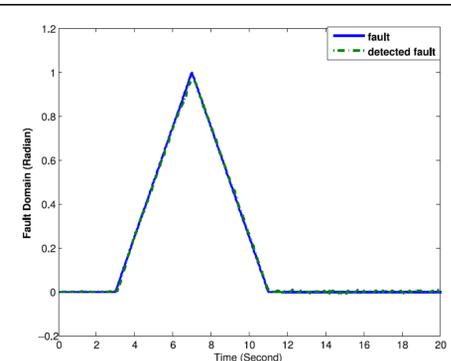


Fig 4: Fault detection using NNAS [2].

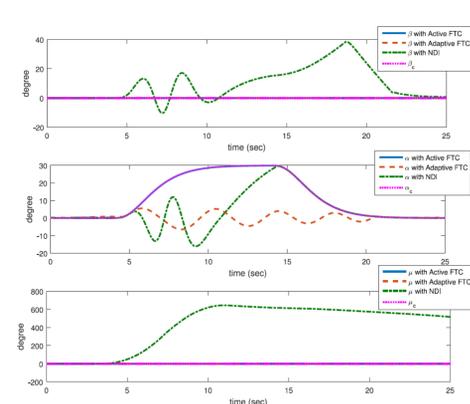


Fig 5: Attitude tracking control of the aircraft in presence of fault in the aileron actuator [2].

Future Work

To overcome the shortcoming of the NNAS, a new model, long short-term memory (LSTM), is proposed. LSTM suggests keeping the overall repeating structure but changing the repeated memory cells. Instead of retaining only the short-term state from the previous few step, the model has an extra vector containing information from the beginning of the model to store the long-term state as shown in Fig. 5.

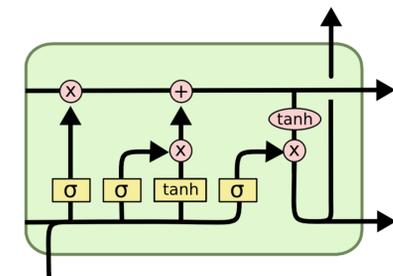


Fig 6: Structure of long short-term memory network (LSTM).

References

1. Fossen, Thor I. Handbook of marine craft hydrodynamics and motion control. John Wiley & Sons, 2011.
2. Abbaspour, Alireza, et al. "Neural adaptive observer-based sensor and actuator fault detection in nonlinear systems: Application in UAV." ISA transactions 67 (2017): 317-329.