Engineering Applications of Artificial Intelligence 52 (2016) 181–193

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Comparison of immunity-based schemes for aircraft failure detection and identification

Dia Al Azzawi [a,1], Hever Moncayo [b,*,2], Mario G. Perhinschi [a,1], Andres Perez [b,2], Adil Togayev [a,1]

[a] West Virginia University, Morgantown, WV 26506, United States
[b] Embry-Riddle Aeronautical University, Daytona Beach, FL 32114, United States

ARTICLE INFO

Article history:
Received 23 November 2015
Received in revised form
6 February 2016
Accepted 28 February 2016

Keywords:
Bioinspired failure detection
Fault identification
Artificial intelligence
Aircraft subsystems failures
Artificial immune system

ABSTRACT

In this paper, two approaches are proposed and compared for the detection and identification of aircraft subsystem failures based on the artificial immune system paradigm combined with the hierarchical multiself strategy. The first approach relies on the heuristic ranking of lower order self/non-self projections and the generation of selective immunity identifiers through structuring of the non-self. The second approach is based on an information processing algorithm inspired by the functionality of the dendritic cells. The artificial dendritic cell is defined as a computational unit that centralizes, fuses, and interprets information from the multiple selves to produce a unique detection and identification outcome. A hierarchical multi-self strategy is used with both approaches considering 2-dimensional self/non-self projections or subselves. A mathematical formulation of the concepts and detailed implementation algorithms are presented. The proposed methodologies are demonstrated and compared using simulation data for a supersonic fighter from a motion-based flight simulator at nominal conditions, under failures of actuators, malfunction of sensors, and wing damage. In all cases considered, both detection and identification schemes achieve excellent detection and identification rates with practically no false alarms.

1. Introduction

Aircraft subsystem failures that result from various sources (such as severe weather conditions, jammed control surfaces, malfunctioning sensors, structural damage during air combat, etc.) may cause catastrophic accidents. Even with the most severe failures, aircraft accident investigations showed that, in many cases, it would have been possible to avoid the accident if the pilot would have taken proper actions at the appropriate time. Although some experienced and highly-skilled pilots can compensate for some failures, they often experience stress and confusion and, therefore, may not take proper actions within few seconds.

Fault-tolerant control strategies have been an extensive research topic in failure accommodation (Zhang and Jiang, 2008; Campbell et al., 2010; Nguyen and Kumar, 2009). However, such strategies often require vital triggering tools that are intelligent enough in gathering the information about the failed subsystem, the nature of the failure, and the severity of the failure as soon as it takes place such that an accommodation strategy identifies which of the remaining resources must be used to accommodate the resulting changes in the system. In fact, this information is important to the pilots too since it represents an alarm tool for their continuous situation awareness.

The existence of a Failure Detection and Identification (FDI) scheme can support automatic accommodation as part of a fault-tolerant control system and it can also improve human accommodation through increased pilot situational awareness. Most of the research efforts in this area have considered only individual failures within limited regions of the flight envelope (Azam et al., 2005; Oonk et al., 2012; Boskovic et al., 2009). State estimation or observer-based schemes have been widely proposed (Wilsky, 1980; Marcos et al., 2002; Shin et al., 2002; Narendra and Balakrishnan, 1997) for actuator FDI relying on Kalman or other classes of filters. Artificial Neural Networks (ANN) have also been extensively used (Napolitano et al., 1996; Jakubek and Strasser, 2002; Lou et al., 2002; Napolitano et al., 2000) to solve the FDI problem for aerospace systems. Alternative approaches for FDI and pilot awareness enhancement were also proposed based on inductive learning (Iverson, 2004).Recent research studies (Belcastro and

* Corresponding author.
[1] Present address: Dept. of Mechanical and Aerospace Engineering, United States.
[2] Present address: Dept. of Aerospace Engineering, United States.

http://dx.doi.org/10.1016/j.engappai.2016.02.017
0952-1976/

Nomenclature

CSM	Co-stimulatory molecules
$\mathbf{D}$	Self/non-self discrimination matrix
Det	Detection outcome
DR	Detection rate
$\mathbf{F}_0$	Non-triggered features matrix
$\mathbf{F}_1$	Triggered features matrix
$F_{1\varphi}$	Current feature-pattern vector
FA	False alarm rate
FP	Feature-pattern vector
$IL10$	Interleukin-10
$IL12$	Interleukin-12
K	Number of cytotoxic T-cells
$\tilde{K}$	Number of residual cytotoxic T-cells
L	Life of a dendritic cell
$\mathscr{M}$	Migration threshold of a dendritic cell
N	Number of features
N_{DC}	Number of dendritic cells
N_k	Number of training samples of sub-system k
N_{MDC}	Number of migrated dendritic cells
N_{RDC}	Number of regulatory dendritic cells
N_s	Number of subsystems
N_{ss}	Number of sub-selves
N_{SDC}	Number of stimulatory dendritic cells
Nft_k	Number of abnormal conditions types of sub-system k
$P(\cdot)$	Probability function
R	Number of suppressor T-cells
$\mathcal{S}$	Sub-self of the system
T	Size of the moving time window
W_{0j}	Non-triggered confidence factor of sub-self j
W_{1j}	Triggered confidence factor of sub-self j

Greek

Δ	Discriminant
$\boldsymbol{\mu}$	Mean vector
$\boldsymbol{\Sigma}$	Covariance matrix
τ	Current sampling time index

Jacobson, 2010; Belcastro, 2010; Roemer et al., 2008; Figueroa et al., 2009), however, have acknowledged the need for an integrated and comprehensive solution to the problem of aircraft FDI, which takes into account the complexity and multidimensionality of aircraft systems.

The issue of sensor FDI has been addressed to a lower extent, since triple and quadruple physical redundancy of aircraft sensors is a common practice. However, sensor FDI schemes based on ANN estimations of sensor outputs have been proposed (Perhinschi et al., 2007; Totah et al., 2007).

Statistical and artificial-intelligence methodologies form the majority of the techniques used in FDI (Hwang et al., 2010). Depending on the technique used, these methods only partially satisfy the FDI requirements of raising minimum false alarms under normal operating conditions, detecting and identifying all subsystem failures with high rates, adapting to system changes, exhibiting robustness to system disturbances and uncertainties, and being scalable to the complexity and dimensionality of the system. A promising candidate in this respect is the Artificial Immune System (AIS) concept (Dasgupta and Attoh-Okine, 1997).

The AIS emerged in recent years as a new computational paradigm in artificial intelligence. The concept has shown a very promising potential for a variety of applications such as anomaly detection (D'haeseleer and Forrest, 1996; Dasgupta and Majumdar, 2002; Forrest et al., 1994; Dasgupta and Forrest, 1999), data mining (Dasgupta and Majumdar, 2002), computer security (Forrest et al., 1994; Gonzalez and Dasgupta, 2003), adaptive control (Farmer et al., 1986; Karr et al., 2005; Ko et al., 2004), and pattern recognition (De Castro and Timmis, 2002a). Although new models and applications are currently being developed (Dasgupta and Attoh-Okine, 1997) and existing methods are improved continuously, the entire field of AIS including negative selection algorithms is still relatively young and not well defined. Theoretical issues have been occasionally addressed in the attempt to assess and prove AIS applicability (Stibor et al., 2006).

In addition, the AIS concept has shown a promising application for fault detection of aerospace systems (Karr et al., 2005; KrishnaKumar, 2003; Sanchez et al., 2009). These efforts have been focused primarily on aircraft systems fault detection and identification; however, they only have considered single classes and high magnitudes of failure for limited regions of the flight envelope. Therefore, the availability of failure detection and identification schemes with high rates of success, with comprehensive coverage, integrating all aircraft sub-systems and operational modes is a critical objective of current research efforts at West Virginia University (WVU) and Embry-Riddle Aeronautical University (ERAU) (Perhinschi et al., 2010; Moncayo et al., 2010; Moncayo et al., 2011a; Moncayo et al., 2011b; Davis, 2010; Davis et al., 2010; Moncayo et al., 2016; Moncayo, 2009; Al Azzawi et al., 2013; Al Azzawi et al., 2014; Al Azzawi, 2014; Perhinschi et al., 2013).

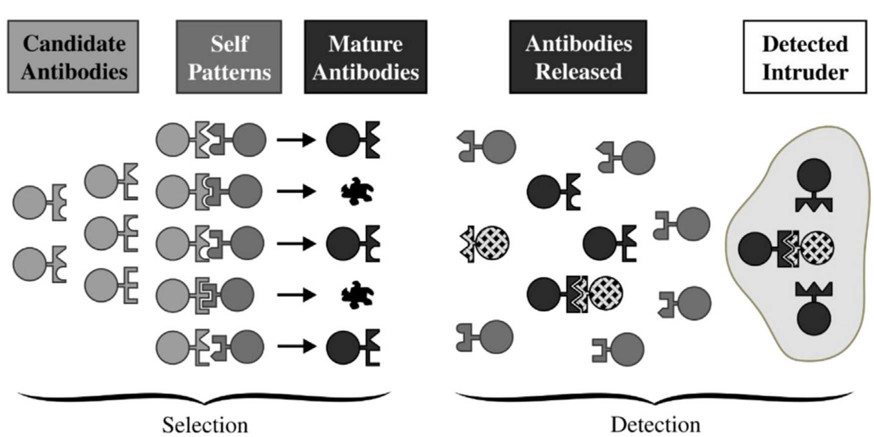

Fig. 1. The negative selection process.