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Immunity-based flight envelope prediction at post-failure conditions

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ABSTRACT

This paper presents the development of a biologically-inspired methodology for flight envelope prediction at post failure conditions. The flight envelope is understood in its most general meaning as the hyperspace of all achievable or desirable relevant variables. The new ranges of these variables at post-failure conditions are the outcomes of the prediction process. Specific algorithms are proposed depending on the affected sub-system and the nature and characteristics of the failure. Actuator, sensor, propulsion system, and structural failures are considered. The proposed methodology is integrated with immunity-based failure detection and identification and benefits from the capabilities of the artificial immune system to address directly the complexity and multi-dimensionality of aircraft dynamic response in the context of abnormal conditions. A hierarchical multi-self strategy is used, in which low-dimensional projections replace the hyperspace of the self thus avoiding numerical and conceptual issues related to the high-dimensionality of the problem. The methodology is illustrated through numerical examples of envelope prediction under elevator locked failure, yaw rate sensor bias, locked throttle, and partially missing horizontal tail.

1. Introduction

Significant research efforts have been focused in the past few years on the development of flight envelope estimation and protection methodologies for aircraft under damage/failure conditions. These efforts were typically addressing isolated specific problems, considering only a reduced number of aircraft dynamic parameters, and performing abnormal condition evaluation or envelope estimation in a limited manner, mostly outside the general context, which also includes abnormal condition detection, identification, and accommodation. Techniques based on obstacle avoidance for prediction of envelope violation have been proposed [1], within which the control/command margins are estimated by forcing a set of limit parameters to track an adaptive safe-trajectory near the limit boundary. Adaptive flight envelope estimation based on on-line learning neural networks has also been investigated and demonstrated with NASA's Generalized Transport Model aircraft in which the command limits of the controller were constantly adapted to allow the aircraft to fly close to its limit boundary under actuator failures [2]. Analytical methods to identify the aerodynamic performance degradation and its impact on the dynamic flight envelope [3] were proposed and demonstrated for different wing/tail lifting surface damage scenarios. Adaptive control laws have been developed to maintain a structurally damaged aircraft within allowable limits and suppress the dynamic structural mode interaction with the flight control system [4]. Reachable sets and the region-of-attraction analysis have been used for flight envelope assessment [5]. The impact of icing on the performance and its mitigation through increased pilot situational awareness have also been investigated [6].

Addressing the problem of aircraft safe operation under abnormal conditions (AC) in a comprehensive manner [7] involves considering the flight envelope with a generalized meaning, as the hyperspace of all achievable or desirable relevant variables in conjunction with the nature and characteristics of the AC. The flight envelope prediction at post-failure conditions can be viewed as part of a more general AC evaluation process, which includes several distinct aspects such as determining the type of the failure (direct qualitative evaluation) and its magnitude or severity (direct quantitative evaluation). In this context, flight envelope prediction can be defined as an AC indirect quantitative evaluation. Successful

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flight envelope prediction requires previous AC detection, identification, and direct evaluation.

A highly effective, integrated, and comprehensive solution to the problem of maintaining control of the aircraft and performing the mission at abnormal flight conditions can only be achieved through a holistic approach that considers the multitude of factors involved (aircraft sub-system abnormalities, external hazards, pilot abnormal conditions, aircraft upset conditions), their variability, versatility, and uncertainty [8,9]. The resulting complexity and multi-dimensionality are enormous. Therefore, an integrated and comprehensive solution to the off-nominal condition detection, identification, evaluation, and accommodation problem for aerospace vehicles requires adequate strategies and tools.

The artificial immune system (AIS) emerged in recent years as a new computational paradigm in artificial intelligence with a variety of applications in areas such as anomaly detection, data mining, computer security, adaptive control, and pattern recognition [10]. Immunity-based fault detection schemes that discriminate between abnormal and normal conditions have been developed [11] inspired by the operation of the biological immune system, which detects exogenous antigens while not reacting to self cells. The versatility, adaptability, and regulatory capabilities of the immune system have inspired the formulation of a comprehensive and integrated immunity-based framework for aircraft abnormal condition detection, identification, evaluation, and accommodation [7,12]. Methodologies for AIS-based detection and identification of a wide variety of aircraft sub-system failures/damages have been designed and implemented [13–15] at West Virginia University (WVU). High-performance AIS-based failure detection and identification schemes have been demonstrated to be capable of handling several categories of sub-system abnormal conditions in flight on a reduced size platform [16]. Testing of the schemes over extended areas of the flight envelope has also been performed successfully [17]. The potential of the AIS paradigm for flight envelope reduction assessment at post-failure conditions has also been investigated with promising results [18].

In this paper, the development of a biologically-inspired methodology for generalized flight envelope prediction at post failure conditions is presented. The prediction process consists of determining ranges of relevant variables at post-failure conditions. Specific algorithms are formulated for several types of actuator, sensor, propulsion system, and structural failures. The proposed methodology is integrated with immunity-based failure detection and identification and benefits from the capabilities of the artificial immune system to address directly the complexity and multi-dimensionality of aircraft dynamic response in the context of abnormal conditions. A hierarchical multi-self strategy is used, in which low-dimensional projections replace the hyperspace of the self thus avoiding numerical and conceptual issues related to the high-dimensionality of the problem.

The general problem of flight envelope prediction is formulated in Section 2. A brief description of the AIS paradigm is provided in Section 3. The issue of integrating abnormal condition detection, identification, and evaluation within the AIS paradigm is addressed in Section 4. Algorithms for flight envelope prediction under actuator, sensor, propulsion and structure failures are presented in Sections 5 through 8, respectively. Example results are discussed in Section 9. Finally, some conclusions are summarized in Section 10, followed by acknowledgements and a bibliographical list.

2. Flight envelope prediction at post-failure conditions

For the purpose of this research effort, the flight envelope is defined as the hyper-space of all achievable or desirable values of a set $\mathcal{E}$ of *envelope relevant variables* (ERV) v_E. Therefore:

$$\mathcal{E} = \{v_{Ei} \mid i = 1, 2, \dots N_E\} \tag{1}$$

Table 1
Feature set.

Feature	Description
H	Altitude
V	Aircraft ground speed
M	Mach number
a_x	Longitudinal acceleration
a_y	Lateral acceleration
a_z	Vertical acceleration
α	Angle of attack
β	Sideslip angle
ϕ	Roll attitude angle
θ	Pitch attitude angle
p	Roll rate
q	Pitch rate
r	Yaw rate
$\dot{p}$	Roll acceleration
$\dot{q}$	Pitch acceleration
$\dot{r}$	Yaw acceleration
d_e	Longitudinal stick displacement
d_a	Lateral stick displacement
d_r	Pedal displacement
d_T	Pilot throttle
p_{ref}	Roll rate command
q_{ref}	Pitch rate command
r_{ref}	Yaw rate command
NN_{outp}	Roll acceleration error
NN_{outq}	Pitch acceleration error
NN_{outr}	Yaw acceleration error
$MQEE$	Main quadratic estimation error [18]
$OQEE$	Output quadratic estimation error [18]
$DQEE_p$	Decentralized quadratic roll rate estimation error [18]
$DQEE_q$	Decentralized quadratic pitch rate estimation error [18]
$DQEE_r$	Decentralized quadratic yaw rate estimation error [18]

Let the *feature variables* or shortly *features* be the variables φ_i that completely define the entire system. The set of all features can be expressed as:

$$\mathcal{F} = \{\varphi_i \mid i = 1, 2, \dots N\} \quad \text{and} \quad \mathcal{E} \subset \mathcal{F} \tag{2}$$

The definition of the feature set $\mathcal{F}$ is a critical element of the AIS implementation. The features must capture the dynamic fingerprint of normal system operation as well as the dynamic fingerprint of all failures considered. For example, the features considered for the purpose of this paper are listed in Table 1.

Let the border hyper-surface of the system operating at normal conditions be:

$$\Sigma(\varphi_1, \varphi_2, \dots, \varphi_N) = 0 \tag{3}$$

Let us restrict the definition of the flight envelope at normal conditions to the set of ranges $[v_{Ei\,min}, v_{Ei\,max}]$ of all envelope variables. If the projection of surface Σ along the axis k defined by φ_k is denoted as $P(\Sigma(\varphi_k))$, then:

$$P\big(\Sigma(\varphi_k)\big) = [v_{Ek\,min}, v_{Ek\,max}] \tag{4}$$

Note that, in general, these ranges can be defined as functions of one or several features. For example, the range of v_{Ek} may be a function of feature φ_l. The projection of surface Σ on the plane (k, l) defined by φ_k and φ_l can be denoted as $P(\Sigma(\varphi_k, \varphi_l))$ and represents the variation of the range $[v_{Ek\,min}, v_{Ek\,max}]$ with φ_l. The flight envelope at abnormal conditions is then defined as the set of ranges of all ERVs at post-failure conditions: $[v_{Ei\,min\,F}, v_{Ei\,max\,F}]$.

Definition: A *directly involved variable* (DIV) v_δ in the AC is a variable whose alteration or abnormal variation is directly and significantly the result of the AC. They may be part of the feature set or not. If they are not, then a relationship between the DIV and some other variable(s) in the feature set must be established. These variables are referred to as *equivalent directly involved variables* (EDIV), v_ε. For example, consider the case of the left elevator