A NEGATIVE SELECTION APPROACH TO DETECT DAMAGE IN AERONAUTICAL STRUCTURES WITH CHANGING OPERATING CONDITIONS

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Abstract

Monitoring the condition of aircraft structures is a vital issue and research is underway to develop new NDE methods based on Vibration-Based Inspection (VBI), offering the potential for detecting faults by monitoring the dynamic characteristics of the structure under test. This article focuses on the possibility to apply the so-called negative selection algorithm inspired by the human immune response to the task of monitoring the integrity of a typical aeronautical structure such as a wing even when its dynamic characteristics vary continuously due to the change in the mass of the fuel system.

1 General Introduction

In the aerospace industry, one fundamental issue that must be addressed concerns monitoring the condition of the structure of the aircraft. Maintenance checks are expensive and inspection for structural damage is usually performed at regular intervals following a specified number of flight hours with the aircraft being taken out of service so that one or more non-destructive ground tests can be conducted. Correspondingly the monitoring of the integrity of the structure is not continuous. Clearly, from this point of view, it would be extremely advantageous to develop sufficiently accurate and reliable techniques which enable the structural integrity of the aircraft to be monitored continuously in-service when operating normally.

In general, the requirement to develop methods for rapid detection of damage in aerospace, mechanical and civil structures is becoming increasingly important and a variety of Non Destructive Evaluation (NDE) methods are currently being investigated for the purpose. Most of these techniques are capable of detecting defects close to the surface of the structure and near the sensor positions.

Of the NDE methods under development, those based on Vibration-Based Inspection (VBI) are currently receiving significant attention, mainly due to the potential for detecting faults at unmeasured locations by monitoring, during the lifetime, the dynamic characteristics of the structure under test. The assumption underlying this category of techniques is that the analysis of the dynamic response and the observation of variations in the characteristic dynamic behaviour of the structure can reveal important information regarding the integrity of the structure, and whether or not defects are present and faults are arising.

For the development of VBI methods applied to structures, biological systems have proved to be a particularly rich source of inspiration and have motivated research into the development and extension to new areas of application of pattern recognition and novelty detection algorithms. The most established class of such algorithms are methods based around the Genetic Algorithm [1]-[3] and Neural Network [4]-[8]. These have been joined recently by a host of new approaches motivated by, among others, Ant Colony Metaphors [9], Swarm Intelligence [10] and Immune System Metaphors [11]. In particular, the construction of the novelty detection algorithm, which is the focus of this article, is based on the ability of the human immune system to discriminate between self and non-self cells [12]-[13].

The resulting *negative-selection algorithm* has recently been applied by Surace and Worden with the purpose of monitoring a system or a structure when the normal condition of it may change due to time-varying environmental or operational conditions; specifically an application of the algorithm has been made to data from a numerical model simulating the dynamic response of an offshore platform with changing mass as a result of variations to the oil storage requirements [14].

On the basis of this previous experience, the research described in this article focuses on the extension of this method to the task of monitoring the integrity of aerospace structures.

As described in this article, one of the advantages of this approach with respect to other VBI methods lies in the fact that an accurate mathematical model of the undamaged structure is non required a-priori: this new technique relies only on a 'description of normality' which is defined in terms of features measured in operational conditions when the structure is known or assumed to be fault-free. For this reason, the method can be applied even to very complex structures which operate in a range of conditions with a corresponding variation in the dynamic characteristics of the structure. For example, in the case of an aircraft in flight, effective mass decreases due to a reduction in fuel and a change in the flight speed.

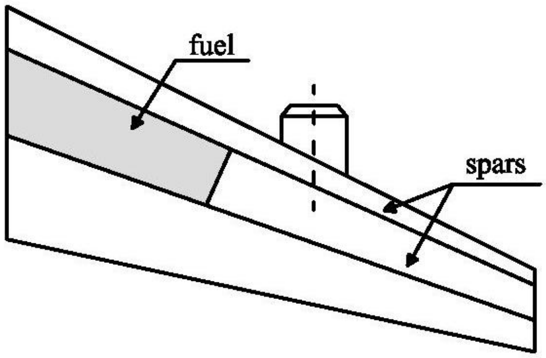

Fig. 1. The wing under study

To demonstrate the validity of the method the dynamic behaviour of the primary structure of a typical transport aircraft (Fig. 1) has been simulated using a finite element model of the wing.

Several mass configurations have been analysed, corresponding to varying amounts of fuel, together with different levels and types of structural damage. Using the results obtained it has been possible to assess the sensitivity of the method to structural alterations and analyse the influence of measurement noise on its effectiveness.

2 Negative Selection Algorithm

The human immune system has the ability to detect *antigens*, i.e. anything which is not part of the body itself, including bacteria, viruses and suchlike. Correspondingly the task of the immune system is to differentiate between antigens and the body itself, a process known as "self/ non-self discrimination", achieved when the invading antigen is ‘‘recognised’’ by a specific antibody called a T-cell receptor.

The T-cell receptors are created by a random genetic rearrangement process. Those cells that successfully bind with self-cells are destroyed in the thymus gland. Only those cells that fail to bind to self-cells are allowed to leave the thymus and become antibodies of the human immune system. Such an antibody-generation-selection process is called *negative selection.*

In a similar way to this negative selection process, novelty detection has the fundamental objective to distinguish between *self* (corresponding to normal operation of the monitored system) and *non-self* (relative to the novel or anomalous states). For this purpose, two sets are considered for the artificial immune system, the self-set S for normal data series and the antibody set D for novelty detectors.

In the past, the patterns used by the negative selection process have been time-series data but, since the method is very general, it can be applied to different kinds of feature vectors such as signals sampled in the frequency domain. In particular in this study, as will be illustrated subsequently, the feature vectors chosen for the purpose of damage detection are transmissibility functions between two points of the monitored structure, measured for each of the different normal conditions.

The self-set data $\mathbf{x\_s}^i$ (for=1,…,n) are obtained by collecting $n=m \times p$ feature vectors where p is the number of times that the same transmissibility function is acquired for each of the m normal operational conditions. Each vector has dimension l, where l is the number of spectral lines.

The antibody set $\mathbf{x\_d}^i$ is built in the following way: a l-dimensional candidate vector **x_c** is generated pseudo-randomly. Then the distance between the candidate and all the vectors in the self-set S is calculated. If the minimum value of all the distances is less than the threshold r_s, then **x_c** is considered to be a normal data segment and is deleted; otherwise **x_c** represents an abnormal data segment. In this case the distance between **x_c** and the vectors in antibody set D is calculated in order to verify if it is matched by any of the vectors in D. The candidate vector belongs to the antibody set only if it fails to match either the vector in S or the detectors in D. This process is repeated for several candidates. Clearly **x_c** will be a new detector without a matching calculation if this is the first candidate detector for D.

If any l-dimensional monitored vector $\mathbf{x\_m}^j$ matches one element of the antibody set D then it must be a non-self-vector and can be classified as novel or anomalous.

According to [12], [13] the cosine similarity has been chosen to measure the distance between two l-dimensional vectors:

$$\mathrm{sim}(\mathbf{x},\mathbf{y}) = \frac{\sum_{i=1}^{l} x_i y_i}{\sqrt{\sum_{i=1}^{l} x_i^2 \sum_{i=1}^{l} y_i^2}} \quad (1)$$

When two vectors are alike, the cosine similarity approaches unity and so the distance defined as:

$$\mathrm{dist}(\mathbf{x},\mathbf{y}) = 1 - \mathrm{sim}(\mathbf{x},\mathbf{y}) \quad (2)$$

tends to 0. So, two vectors match when their distance is less then the matching threshold.

For the self-set data S, if λ_s^i is the minimum distance between vector $\mathbf{x\_s}^i$ and the other vectors within S and λ_s is the maximum among all λ_s^i , then the matching threshold r_s must be chosen greater than λ_s, to avoid false positives, but not too great to avoid false negatives.

As regards the matching threshold for the antibody-set data, each detector $\mathbf{x\_d}^i$ has its own matching threshold $r_d^{\,i}$ calculated following the approach of [12], [13].

3 Model of the Wing

The mathematical model of the wing is the one presented in [15], [16]. The wing is modelled as a one-dimensional structure with composite upper and lower panels.

To build the model, a typical segment of the wing eg. from rib to rib has been isolated and then trasformed into a wing-box element (Fig. 2).

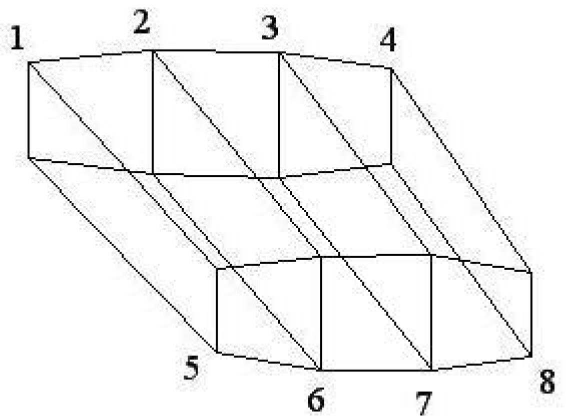

Fig. 2. The wing-box element

Subsequently this element has been considered as a beam, with a cross section that has variations from one end to the other such as in the geometrical properties of the stringers and the skins. The built-up structure consists of a curved bottom and laminated skins, four webs and eight stringers as in Fig. 2. In accordance with the classical empirical rules of aeronautical engineering, webs are assumed to support only shear stresses, while skins are only subjected to axial stresses. Following the Timoshenko theory, both transverse shear and a correction factor which takes into account the warping restraints induced by the boundary conditions, are included in the formulation. Morover the properties of members which are not present in the lay-up, eg. webs or stringers, can be set to zero.

The wing model considered in this article has the following geometrical characteristics and mechanical properties:

- Wing span of 26.6 m;
- Chord of 5.223 m at root and 1.272 m at tip;
- Sweep angle of –24° (backward);
- Two webs;
- Eight stringers;
- Alluminium as a material for all the elements of the structure;
- One engine with mass M_E= 2000kg located in the middle of the wing.

4 Normal Conditions and Damage Cases

To simulate real operational conditions, the change in the fuel mass stored in the wing is assumed to be a variable parameter such that it introduces a variation in the dynamic behaviour of the wing i.e. different operational configurations. In particular, 10 different configurations were considered: in the first configuration a fuel mass of 4111.1 kg is stored in the wing, while in the tenth configuration the fuel mass is equal to 4384.0 kg. Consequently the difference in mass between two adjacent configurations is of 0.62%, referred to 4384.00 kg, which is sufficiently low to consider these ten configurations as a continuous variation in the mass of the structure.

The wing is discretised with eight elements, as shown in Fig.3, and the fuel mass is introduced as concentrated masses without rotational inertia at nodes no. 2, 3 and 4 with a value of 5/12 M_f, 1/4 M_f and 1/12 M_f respectively, where M_f is the mass of the fuel.

Using the finite element method, the equation of motion of the structure can be written as:

$$\mathbf{K}(1+i\eta)\,\mathbf{y}+\mathbf{M}(\mathbf{M}_f)\,\ddot{\mathbf{y}}=\mathbf{F} \qquad (3)$$

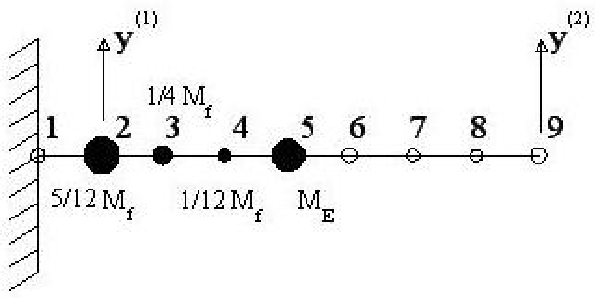

Fig. 3. Positions of concentrated masses and sensors on the model of the wing

where η=0.02 is the structural damping. The equation highlights that the dynamic behaviour of the structure is function of the fuel mass M_f.

The variation in natural frequencies of the wing due to the change of the mass fuel during the flight is shown in Table 1.

		f_1 [Hz]	f_2 [Hz]	f_3 [Hz]	f_4 [Hz]
Configuration n°	1	2.353	8.833	19.428	33.365
	2	2.353	8.825	19.397	33.308
	3	2.353	8.816	19.366	33.252
	4	2.353	8.807	19.335	33.197
	5	2.353	8.798	19.305	33.142
	6	2.353	8.790	19.275	33.088
	7	2.353	8.781	19.245	33.034
	8	2.353	8.772	19.215	32.981
	9	2.353	8.764	19.186	32.929
	10	2.353	8.755	19.157	32.877

Table 1. First four natural frequencies of the wing for the different configurations

It is evident that the first natural frequency does not change with the variation due to the fuel mass, while the other frequencies have a variation that is 1.4%, 2.2% and 2.3% for the second, the third and the fourth mode, respectively. As a consequence, the modification in the dynamic behaviour of the structure can be approximated by a continuous variation, as previously described for the mass variation.

In order to investigate the effect of different types of damage on the dynamic behaviour of the structure under test, two kinds of faults have been considered:

1) reduction of the stiffness of one web of the element nearest to the clamped end of the wing.
2) Reduction of the stringer 1 (see Fig. 2) for the element nearest to the clamped end of the wing (this case is equivalent to decrease the stiffness of the spar-flange).

Each damage is induced by directly reducing the elemental Young's moduli by an appropriate percentage. Furthermore damage of varying extent is introduced into the web and the stringer, as shown in Table 2:

Damage in the web			Damage in the spar-flange		
A	B	C	D	E	F
10%	20%	30%	10%	20%	30%

Table 2. Stiffness reduction for the different damage cases

Damage cases	f_1 [Hz]	f_2 [Hz]	f_3 [Hz]	f_4 [Hz]
A	2.353	8.832	19.413	33.326
B	2.353	8.831	19.397	33.287
C	2.353	8.830	19.382	33.246
D	2.351	8.810	19.403	33.342
E	2.348	8.784	19.376	33.317
F	2.344	8.755	19.346	33.289

Table 3. First four natural frequencies of the wing in configurations 1 for the different damage cases

In Table 3 the first four natural frequencies of the wing in configuration 1, i.e. with the minimum quantity of fuel and damaged according to Table 2, are presented. The maximum variation of natural frequencies is equal to –0.883% in the case of mode 3 and damage case F. This variation is very low and can be confused with the variation due to a change in the mass of fuel.

5 Application of the algorithm and results

In order to detect damage, the response transmissibility functions in terms of transverse displacement were calculated for different locations along the structure with respect to excitation applied at node 9, for all ten operational conditions.

It is evident that damage should influence the functions measured at each of the response locations in a different way. Therefore, in order to illustrate the general applicability of the technique, the transmissibility function between the two measurement points which are the furthest apart on the structure (sensors 2 and 9) has been selected to apply the damage detection method, in order to encompass the dynamics of the entire beam.

The self-set $\mathbf{x\_s}^i$ is a collection of 3000 feature vectors obtained by making 300 identical copies of the transmissibility functions between points 9 and 2 corresponding to the undamaged structure for each of the ten operational conditions. Then each of these functions has been polluted differently with 1% additive Gaussian noise.

An antibody set of 30 detectors $\mathbf{x\_d}^j$ has been determined, using the self-set constructed by the negative selection algorithm.

The monitored set $\mathbf{x\_m}^i$ is a collection of 3300 feature vectors, the first 3000 are relative to the four normal conditions and the last 300 are polluted copies of the transmissibility functions between points 9 and 2 relative to the damaged structure.

The affinity between the $\mathbf{x\_m}$ and $\mathbf{x\_d}$ is evaluated calculating the Novelty Index *NI* in the following way:

$$NI(i) = \min\left[\mathrm{dist}(\mathbf{x\_m}^i, \mathbf{x\_d}^j) - r_d^{\,j}\right] \qquad (4)$$

For a negative value of *NI* the corresponding data segment is novel or anomalous.

In figures from 4 to 9, the Novelty Index is plotted for the different cases of damage. The first 3000 points represent the index for the ten different normal condition and it possible to see that the index is positive meaning that the

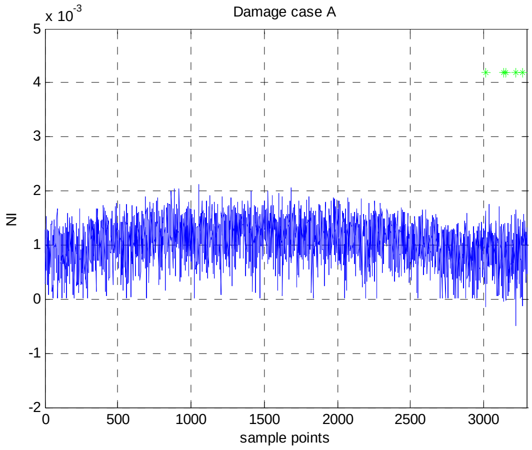

Fig. 4. Novelty index for damage case A

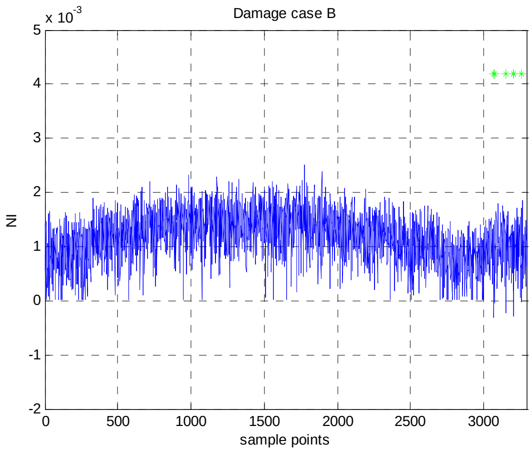

Fig. 5. Novelty index for damage case B

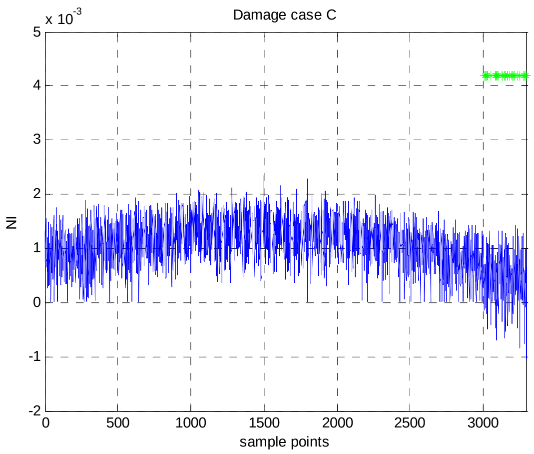

Fig. 6. Novelty index for damage case C

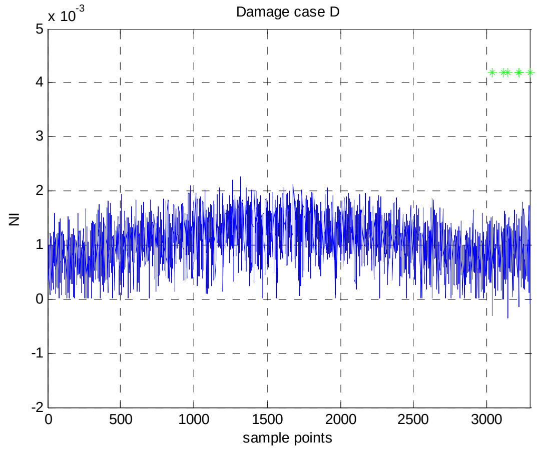

Fig. 7. Novelty index for damage case D

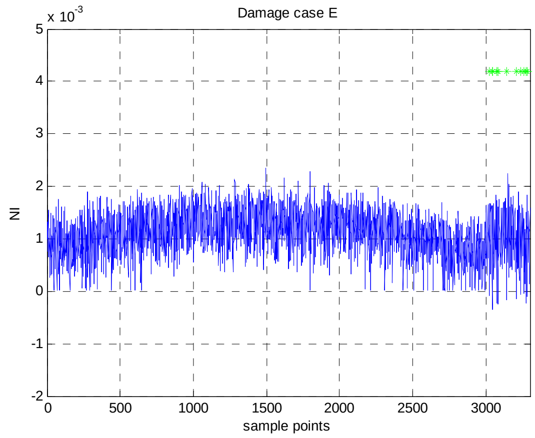

Fig. 8. Novelty index for damage case E

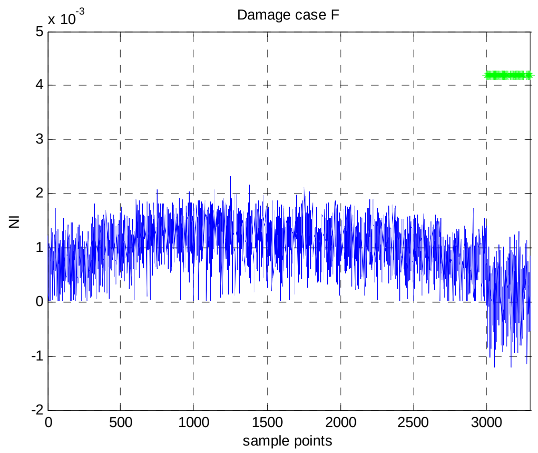

Fig. 9. Novelty index for damage case F

algorithm correctly does not find any segment as anomalous. The green stars on the data from 3001 to 3300 represent values of negative *NI*.

6 Discussion and Conclusions

The results of this study show that the negative selection algorithm is capable of distinguishing various damage conditions in a model structure, from a number of inequivalent normal conditions induced by time-varying fuel storage. On the contrary, the changes in natural frequency as a result of taking on fuel can be mistaken with the changes due to damage. This marks the algorithm as one of the more versatile of the novelty detection class, able to deal with non- Gaussian clusters of normal condition data. A simple but important aspect of this paper is the use of general feature vectors as opposed to the windowed time-series data used in previous studies with the immune system metaphor. Again, the algorithm has no difficulty with the extension. It remains to be seen how the algorithm will perform in severely non-Gaussian situations, i.e. disconnected normal condition sets; however, the geometry of the method suggests that it will be able to cope and this will be the subject of further work.

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