Data-driven State Awareness for Fly-by-feel Aerial Vehicles: Experimental Assessment of a Non-parametric Probabilistic Stall Detection Approach

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ABSTRACT

In this work, an experimental study of a novel data-driven fly-by-feel state awareness method is presented. A non-parametric probabilistic approach for stall detection is investigated and assessed via a series of wind tunnel experiments. The method is based on the statistical analysis of the recorded signals and subsequent statistical hypothesis testing and decision making procedures. In this proof-of-concept experimental study, the flight state is defined by two variables, the airspeed and angle of attack. The experimental evaluation and assessment is based on a prototype bio-inspired self-sensing composite wing that is subjected to a series of wind tunnel experiments under multiple flight states. Distributed micro-sensors, in the form of stretchable sensor networks, are embedded in the composite layup of the wing in order to provide the sensing capabilities. Experimental data collected from piezoelectric sensors are employed for the development and assessment of a non-parametric fly-by-feel stall detection approach within a probabilistic framework. In this study, special emphasis is given to the early detection of aerodynamic stall without making use of any conventional information related to the attitude of the vehicle. The method is able to provide in real time the probability of stall for an indicative flight scenario that was implemented in the wind tunnel. The obtained results demonstrate the effectiveness and potential of the developed approach.

INTRODUCTION

The next generation of intelligent aerospace structures and aerial vehicles will be able to “feel”, “think”, and “react” in real time based on high-resolution state-sensing, awareness, and self-diagnostic capabilities. One of the main challenges of the current state-of-the-art research is the development of technologies that will lead to autonomous “fly-by-feel” aerial vehicles inspired by the unprecedented sensing and actuation capabilities of biological systems. Such intelligent air vehicles will be able to (i) sense the external environment (temperature, air pressure, humidity, etc.) [1], (ii) sense their flight and aeroelastic state (airspeed, angle of attack, flutter, stall, aerodynamic loads, etc.) and

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internal structural condition (stresses, strains, damage) [2–4], and (iii) effectively interpret the sensing data to achieve real-time state awareness and health monitoring [5–9]. Towards this end, novel data-driven approaches are needed for the accurate interpretation of sensory data collected under varying flight states, structural conditions, and uncertainty in complex dynamic environments.

The most critical challenge for the postulation of a complete and applicable data-driven state-awareness framework is the effective modeling and interpretation of data recorded in dynamic environments under multiple flight states and varying structural health conditions. For aerial vehicles, the investigation of the aeroelastic response requires careful consideration throughout the design phase of the air vehicle and poses a major factor in the qualification of aircraft into service [10–16]. It is therefore evident that the flight states and operating conditions –characterized by one or more variables, such as airspeed, angle of attack (AoA), altitude, temperature, humidity, icing, and so on– may vary over time, and consequently affect the system dynamics and aeroelastic response. In such cases, the issue of the accurate data analysis, modeling, and interpretation under varying flight states remains a critical one that needs to be properly addressed within the fly-by-feel concept.

The traditional aircraft control and guidance approaches are based on the use of attitude information obtained via traditional sensors, such as inertial measurement units, global positioning systems (GPS), as well as angle of attack (AoA), pressure, and airspeed sensors. Using this information and corresponding processing methods, the pilot or aircraft controller/computer enables appropriate control actions in order to ensure that the aircraft complies with its flight envelope, that has been predetermined during the design phase. In this conventional control approach, the aircraft state awareness remains limited to the attitude information and no further knowledge on the structural and aeroelastic response is necessary. However, within this context, the aircraft design as well as the performance capabilities remain strictly confined within the flight envelope due to the lack of structural awareness, and oftentimes are rather conservative in order to ensure the safety of the system. On the other hand, the "fly-by-feel" concept aims at the development of methods that –inspired by avian flight– leverage the aircraft structural and aeroelastic awareness via the use of appropriate sensing, modeling and data-driven analysis techniques in order to exploit the full range of aircraft performance capabilities while ensuring the structural safety via complete real-time monitoring of the vehicle. Eventually, such fly-by-feel vehicles constitute the use of conventional flight envelopes obsolete, as flight is governed by unprecedented state sensing and structural awareness.

The **aim** of the present study is the introduction and experimental evaluation of a novel data-driven fly-by-feel state awareness method for stall detection. The method is based on the statistical analysis of the response signals recorded from piezoelectric sensors integrated with the aircraft structure and the subsequent use of decision making schemes to detect stall within a probabilistic framework. The experimental evaluation and assessment is based on a prototype bio-inspired self-sensing composite wing that is subjected to a series of wind tunnel experiments under multiple flight states [2, 4].

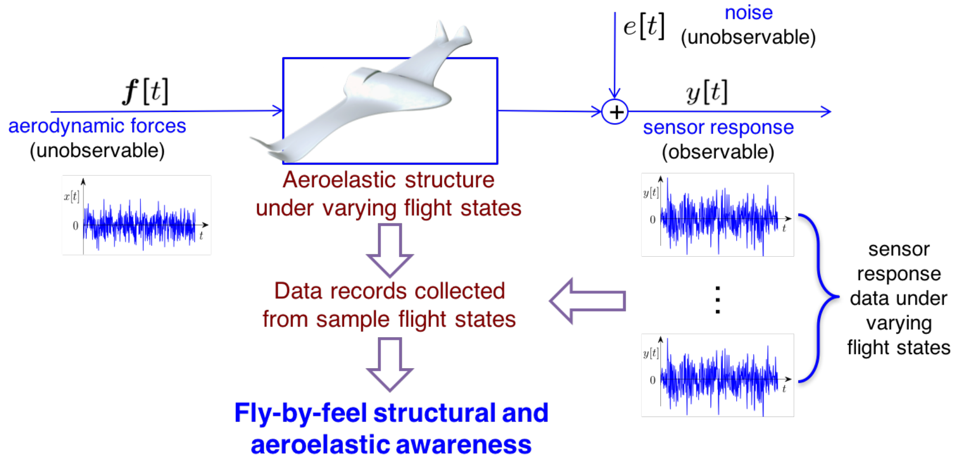

Figure 1. Fly-by-feel structural and aeroelastic awareness via the use of noise-corrupted data records obtained under a sample of all the admissible flight states.

PROBLEM STATEMENT AND METHOD OF APPROACH

The problem statement of this work is as follows: Given dynamic noise-corrupted response-only data records collected from a sample of the admissible flight states, with each state characterized by a specific airspeed and AoA and kept constant for the duration of the data collection, develop appropriate fly-by-feel methods capable for monitoring and detecting aerodynamic stall without the use of attitude information. Figure 1 depicts a schematic representation of the proposed fly-by-feel framework[1].

In order to achieve the experimental evaluation and assessment of the proposed framework, a prototype proof-of-concept self-sensing composite UAV wing was designed and fabricated [2, 4]. The wing is outfitted with bio-inspired stretchable sensor networks [1, 19] consisting of distributed micro-sensors that enable self-sensing capabilities. The sensor networks are embedded inside the composite layup of the wing leaving a minimal parasitic footprint on the mechanical properties. In this work, piezoelectric sensors are used to sense the aeroelastic response (vibration) of the wing and allow the development of fly-by-feel approaches. A series of 266 wind tunnel experiments, with each corresponding to a distinct AoA and airspeed pair, are conducted for collecting data under a broad range of flight states. The obtained data are used for the subsequent analysis, comparison and assessment of the developed approaches.

THE BIO-INSPIRED COMPOSITE WING AND THE EXPERIMENTS

The prototype bio-inspired self-sensing composite wing was designed and fabricated at Stanford University (Figure 2). It is outfitted with micro-fabricated multi-modal distributed sensor networks that have been embedded between the carbon-fiber and fiber-

[1]The morphing aerial vehicle shown in Figure 1 is based on artist's rendering of the 21st Century Aerospace Vehicle as envisioned by NASA for a morphing aircraft of the future. See https://www.dfrc.nasa.gov/Gallery/Photo/Morph/index.html.

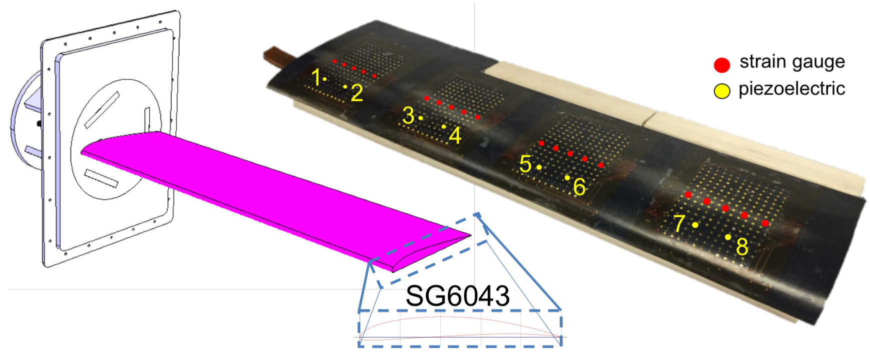

Figure 2. The wing airfoil and the locations of 8 piezoelectric and 20 strain sensors.

glass layers of the top composite skin of the wing structure. The stretchable networks used in this study consist of piezoelectric [20, 21], strain [20], temperature [20, 22], and pressure sensors, and are embedded between the layers of the composite material. In this work, four stretchable multi-modal sensor networks have been designed and fabricated so that they can be embedded inside the composite layup of the top skin of the wing. Each of the four sensor networks contains 8 piezoelectric sensors (disc PZT 3.175 mm in diameter), 6 strain gauges, and 24 RTDs. The total number of embedded sensors in the composite wing is 148. The wing design is based on the cambered SG6043 high lift-to-drag ratio airfoil with a 0.86 m half-wingspan, 0.235 m chord, and an aspect ratio of 7.32. The composite wing structure was manufactured from carbon fiber and fiberglass laminated composites. The wing skin layup consists of carbon fiber (CF) plain weave fabric 1K T300 and fiberglass (FG) plain weave fabric 18 gr/m^2 infused with Araldite LY/HY5052 epoxy. The stacking sequence of the layers is [0^o FG, 0^o CF, 45^o CF, 45^o CF, 0^o CF, 0^o FG].

The Experiments

The prototype composite wing was tested in the open-loop low-turbulence wind tunnel facility at Stanford University. The wind tunnel has a square test section of 0.84 $\times$ 0.84 m (33 $\times$ 33 in) and can achieve continuous flow speeds up to approximately 30 m/s. The wing was mounted horizontally inside the test section using an aluminum rod (2.54 cm diameter) that connected the wing with the basis (see Figure 2). Figure 2 shows the design of the wing basis and presents the locations of 8 piezoelectric and 20 strain sensors on the composite wing.

A series of wind tunnel experiments were conducted for various AoA and airspeeds U_∞. For each AoA, spanning the range from 0 to 18 degrees with an incremental step of 1 degree, data were sequentially collected for all velocities within the range 9 m/s to 22 m/s (incremental step of 1 m/s). The above procedure resulted to 266 different experiments covering the complete range of the considered flight states. For each experiment the vibration response was recorded at different locations on the wing via the embedded piezoelectric sensors. The signals were recorded via a National Instruments X Series 6366 data acquisition module featuring eight 16-bit simultaneously sampled analog-to-digital channels. Table I summarizes the piezoelectric data acquisition, signal, and pre-processing details.

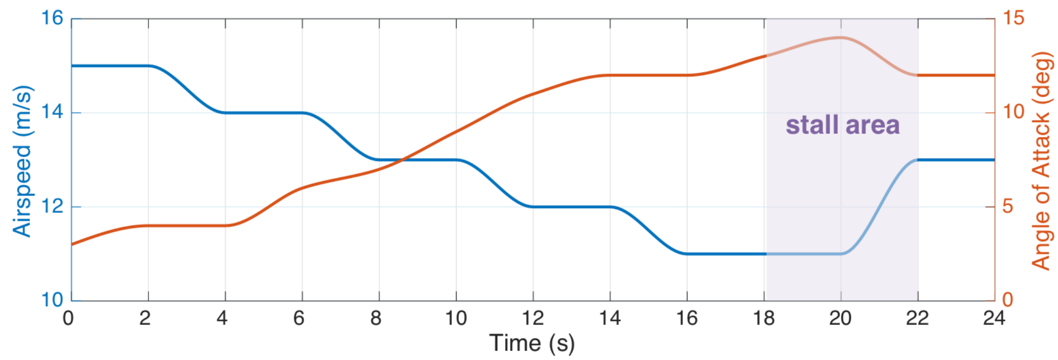

Figure 3. Indicative signals obtained from piezoelectric sensor 1 under various angles of attack: (a) freestream velocity $U_\infty = 11$ m/s and (b) freestream velocity $U_\infty = 15$ m/s.

EXPERIMENTAL RESULTS

The experimental assessment of the fly-by-feel methods is based on the stall scenario of Figure 3 that was implemented during the wind tunnel experiments. The duration of each flight state is 2 s, while stall occurs from 18 s to 22 s and is indicated by the shaded area in Figure 3. Based on the 266 experiments under the considered flight states, the goal is to develop a robust fly-by-feel approach that is capable of monitoring and detecting aerodynamic stall. Figure 4 presents an indicative wind tunnel piezoelectric signal obtained from sensor 1. Observe the stochastic (random) and time varying nature of the signal. In addition, it is evident that as the wing approaches stall, the signal amplitude and standard deviation change (compare with Figure 3).

Non-parametric Signal-Energy Based Stall Detection

In order to investigate the signal amplitude and standard deviation of the signals with respect to varying AoA and airspeed we conducted the statistical signal energy analysis. The interested reader may refer to [4] for a detailed analysis. The initial signal of 90 s ($N = 90,000$ samples) was split into signal windows of 0.5 s ($N = 500$ samples) each and the mean value and the standard deviation of the signal energy were estimated.

Figure 5 presents indicative signal energy results obtained from piezoelectric sensor 3 during the wind tunnel experiments. The left subplot corresponds to a constant AoA of 3 degrees for increasing airspeed. Observe the quadratic increase in the signal energy with respect to increasing airspeed. As the airspeed increases the confidence bounds also

TABLE I. DATA ACQUISITION AND SIGNAL PRE-PROCESSING DETAILS.

Number of sensors:	8
Sampling frequency:	$f_s = 1000$ Hz
Signal length:	$N = 90,000$ samples (90 s)
Initial Bandwidth:	$[0.1 - 500]$ Hz
Filtering:	Low-pass Chebyshev Type II (12th order; cut-off frequency 80 Hz)
Filtered Bandwidth:	$[0.1 - 80]$ Hz

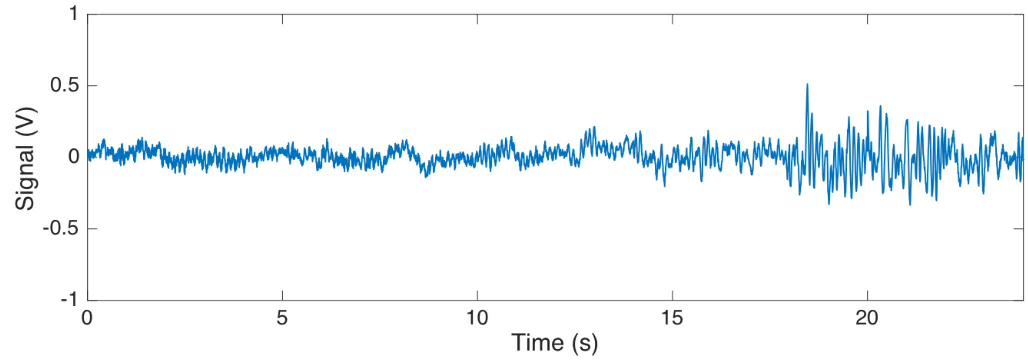

Figure 4. Indicative signals obtained from piezoelectric sensor 1 under various angles of attack: (a) freestream velocity $U_\infty = 11$ m/s and (b) freestream velocity $U_\infty = 15$ m/s.

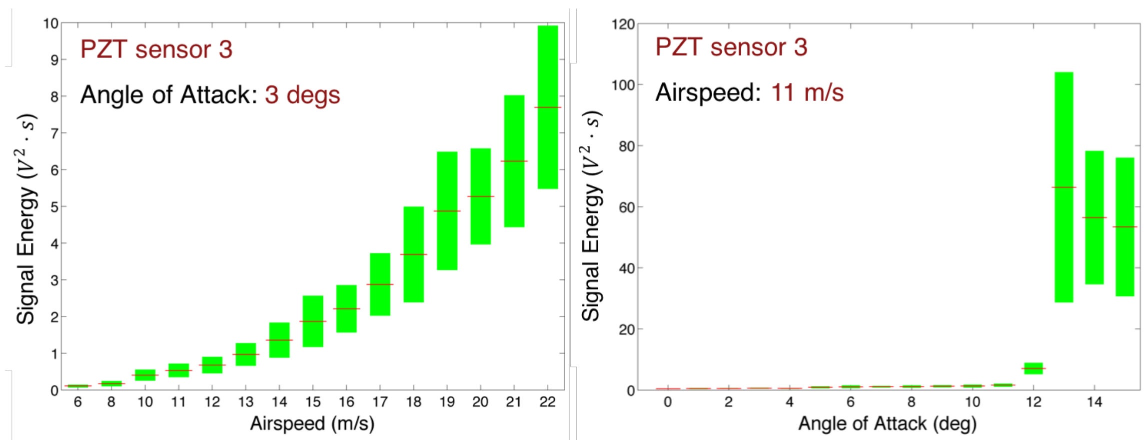

Figure 5. Indicative signal energy versus airspeed and constant AoA of 3 degrees (left), and signal energy versus AoA and constant airspeed $U_\infty = 11$ m/s (right) for piezoelectric sensor 3. The mean values of the signal energy are shown as red lines. The 99% confidence bounds are shown as green shaded areas.

increase. The left subplot presents the AoA between 0 and 15 degrees for q constant airspeed of $U_\infty = 11$ m/s. The goal is to correlate the signal energy in the time domain with the airflow characteristics and aeroelastic properties in order to identify and track appropriate signal features that can be used for early detection of stall under various flight states. Figure 5 presents the mean value of the vibrational signal energy along with the 99% confidence bounds.

For the case $U_\infty = 11$ m/s (right subplot in 5) as the AoA exceeds the value of 12 degrees the signal energy significantly increases and reaches the maximum value as it approaches stall (AoA of 13 degrees). Then, it slightly decreases after stall has occurred (14 and 15 degrees). The sudden increase in the signal energy is caused by the stall-induced oscillations. The statistical analysis of the wind tunnel signals for the various sensors indicated that for velocities in the range of 10 m/s to 12 m/s the stall angle lies within 12 to 13 degrees, whereas for higher velocities the stall AoA may exceed the 15 degrees.

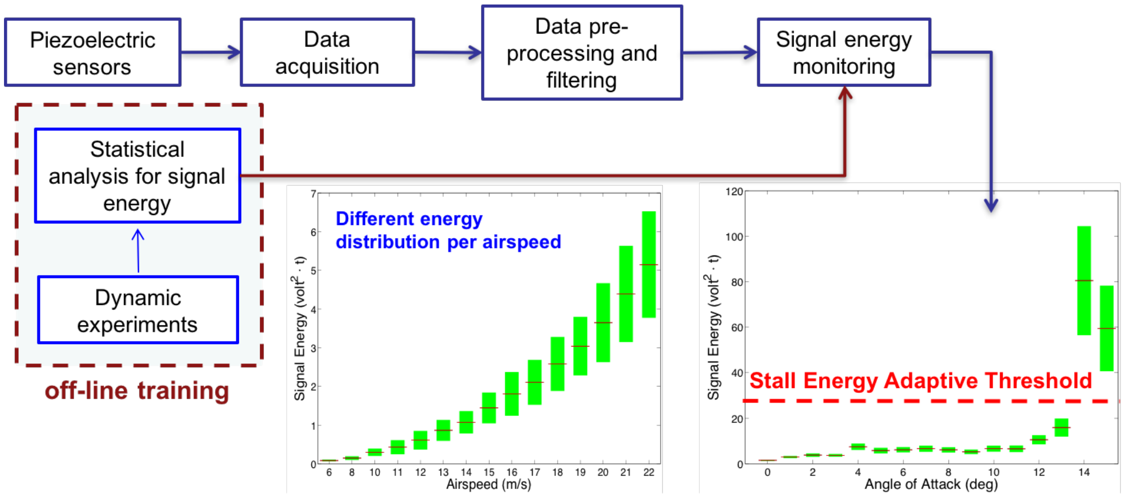

Figure 6. Schematic representation of the non-parametric signal energy based approach for fly-by-feel stall detection. The off-line stage is shown within the dashed rectangular area.

Based on these observations, it is possible to estimate the statistical energy distribution for each flight state as defined by the airspeed and AoA. In this case, assuming data stationarity under each flight state and slow evolution of the wing dynamics, and without loss of generality, the signal energy follows normal distribution. Next, by defining appropriate arbitrary or adaptive (depending on the airspeed) thresholds related to the signal energy under stall, it is possible to postulate appropriate deterministic or probabilistic stall detection approaches without the need to use flight envelope or aircraft attitude information.

Figure 6 presents the block diagram of the developed non-parametric approach that is implemented in two stages: (i) the off-line stage during which training data is collected via appropriate experiments or high-fidelity aeroelastic simulations and the signal energy statistical distributions are established for varying flight states; and (ii) the on-line stage during which the stall detection monitoring takes place in real-time via the use of a constantly adaptive threshold that is based on the aircraft airspeed. The on-line stage requires the algorithm initialization via a short time window in the order of a few seconds. In this case, an initialization window of 1 s was selected.

The adaptive threshold depends on the airspeed at each time instant and its value can be determined as the lower confidence interval of the stall angle signal energy statistical distribution at the desired confidence level $1 - \alpha$. In practice, oftentimes α takes values of 5% or 1% leading to confidence levels of 95% or 99%, respectively. The selection of an appropriate adaptive threshold depends on the desired safety margins as well as maneuvering, control, and recovering capabilities of the aircraft. In this preliminary study, an indicative confidence level of 99% is selected.

Figure 7 presents indicative stall detection results from the flight scenario of Figure 3 based on the recorded piezoelectric signal of Figure 4. In the top subplot of Figure 7 the signal energy is monitored in real time with an update interval of 2 ms. Based on the airspeed value, at each time interval the threshold is indicated as a red dashed line and is extracted based on the underlying signal energy distribution that is available from the off-

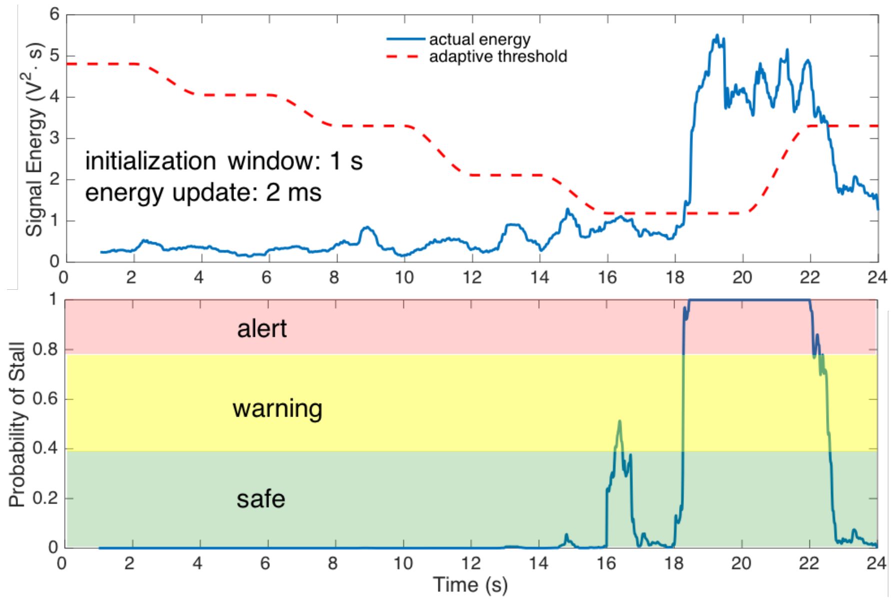

Figure 7. Stall detection results based on the non-parametric signal energy adaptive threshold method. The signal energy is plotted versus the adaptive airspeed-based threshold (top subplot), and the probability of stall versus time (bottom subplot).

line training phase. As the wind approaches stall the signal energy increases while the adaptive threshold decreases with decreasing airspeed (also see Figure 3). Remarkably, after 18 s the wing is under stall and this is indicated by the signal energy that exceeds the threshold. As the wing remains under stall until 22 s, the signal energy exceeds the threshold during this time period. After 20 s, the airspeed starts to increase as the wing is trying to recover and this is also indicated in the adaptive threshold that also starts to increase. When time exceeds 22 s the wing recovers and the signal energy falls again below the threshold.

Although the adaptive threshold approach provides an immediate and clear indication of stall, it is based on a binary statistical decision making scheme, i.e. the wing is under stall or no stall. Therefore, in order to provide a more informed stall monitoring and warning approach capable of enabling different levels of alerting, based on the estimated statistical distributions it is possible to calculate the probability of stall. The bottom subplot of Figure 7 presents the probability of stall versus time for the same stall scenario. The probability of stall is shown as solid line, whereas the three shaded areas correspond to three levels of alerting, namely the safe, warning, and alert regions. Similarly to the top subplot, the probability of stall is close to zero until 18 s, while there is an abrupt change that reaches 0.4 between 16 s and 17 s. Next, the probability of stall increases to 1 at 18 s to 22 s, when again decreases as the wing recovers.

CONCLUDING REMARKS

In this work, an experimental study of a novel data-driven fly-by-feel method for stall detection was presented. The developed non-parametric probabilistic approach was investigated and assessed via a series of wind tunnel experiments. The method's cornerstone is based on the off-line training and statistical analysis of the recorded signals and subsequent on-line real-time statistical hypothesis testing and decision making procedures. In this study, the flight state is defined by two variables, the airspeed and angle of attack. The experimental evaluation was based on a prototype bio-inspired self-sensing composite wing that was subjected to a series of wind tunnel experiments under multiple flight states. The non-parametric approach was implemented in two stages: (i) the off-line stage during which training data is collected via appropriate experiments or high-fidelity aeroelastic simulations and the signal energy statistical distributions are established for varying flight states; and (ii) the on-line stage during which the stall detection monitoring takes place in real-time via the use of a constantly adaptive threshold that is based on the aircraft airspeed. The method was shown to effectively tackle stall monitoring and detection within a probabilistic framework without using wing attitude information. The results indicated that the early detection of stall can be effectively achieved via monitoring of the real-time extraction of the probability of stall.

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