

# Frequency Domain Method for Real-Time Detection of Oscillations

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**Because of the growing interest in real-time stability monitoring, there is a need for online methods that can detect off-nominal behavior in control systems. Therefore, we present a real-time frequency domain method for detecting oscillations in control systems. The method uses recursive Fourier transform for representing the measured time-domain signal in frequency domain. Oscillations are then detected by monitoring the norm of the Fourier coefficients over a time window of prespecified size across a range of frequencies that represent off-nominal behavior for the plant. The method is computationally efficient and requires little memory, and hence suitable for online application. The feasibility of using this method for a real-time detection of oscillation is demonstrated on the Georgia Tech Twinstar Unmanned Aerial System.**

## I. Introduction

REAL-TIME stability monitoring is becoming an important area of research as autonomous systems continue to take on increasing responsibilities. Control technologies are currently being developed to detect and mitigate ill effects of system failures. The Intelligent Resilient Aircraft Control project is an excellent example of recent such efforts to increase the safety of aerospace systems in adverse environments [1]. The ability to monitor the health of onboard systems and to assess the effectiveness of control action in real-time aids greatly in preventing and recovering from the loss of control situations, including control-induced oscillations. The detection of such oscillations is an important aspect of system health and stability monitoring that cannot be addressed by monitoring only the instantaneous system state or the tracking error.

Oscillations in systems states can be control-induced. For example, it is well known that high gains in linear controllers may lead to control system induced oscillations. Furthermore, it is also well known that adaptive systems are susceptible to the “bursting” phenomenon, which is characterized by intermittent high-frequency oscillations and is a result of large adaptation gain [2]. Such induced oscillations can lead to a variety of undesirable phenomena including actuator saturation, excitation of unmodeled dynamics, and loss of system stability. Early detection and mitigation of these effects are extremely important in assuring safe operation and optimal performance. For example, in autopilot systems for modern flight vehicles, fast and efficient detection of oscillations is imperative to prevent the deterioration of ride quality and to minimize the possibility of systems’ failure.

Several methods have been proposed in the literature for detecting oscillations and their characteristics. Miao and Seborg [3] studied a statistically based off-line approach in which the dependence of time-series data was characterized

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using sample auto-correlation coefficients. The decay ratio of these coefficients was used as an indicator to determine whether the signal was excessively oscillatory. Thornhill et al. [4] studied the use of zero-crossing of filtered auto-correlation functions for detection of oscillations at different frequencies in process control loops. Both these methods require an integral of the data over a finite time window and hence do not lend easily to real-time implementation. Korba et al. [5] proposed a Kalman-filter-based method for a real-time estimation of the oscillatory modes in a system using measured data. The dominant frequency and damping of the oscillatory modes were estimated from the measured data by estimating the eigenvalues and eigenvectors of the state matrix of a linearized model. However, if the underlying controller or dynamics do not yield to a linear model, the eigenvalue estimates may not converge.

Cox et al. [6] developed a neural-network (NN)-based algorithm for detecting and compensating Pilot-Induced Oscillations. An NN-based discrimination function was trained using a gradient-descent-like method to indicate the presence of oscillations. This method needs an explicit storage of a window of data; furthermore, the reliability of this method is dependent on the convergence of the gradient descent method for NN training, which in turn depends on the number of unknown NN weights and the excitation in the system signals [2]. Odgaard and Wickerhauser [7] developed a method wherein the principal components of a signal could be obtained using Karhunen–Loeve analysis. This analytic method was used to detect as well as localize the oscillation to specific measurements/sensors. This method is suitable primarily for offline analysis and is computationally intensive to implement online.

Harris et al. [8] compared the variance of the signal with the lowest achievable variance of the control loop. A priori knowledge of the latter, which is hard to obtain, is needed to set a threshold value. Adami et al. [9] presented an instability, indicator based on Lyapunov’s first method. The indicator can be used to indicate whether the system is moving away from the equilibrium state. This method, however, is concerned more with the detection of instability and the presence of persistent oscillations in the system could give rise to incorrect information. Thompson et al. [10] developed wavelet-based methods for detecting loss-of-control in real-time applications. In this method, the time-domain signal was decomposed into basis functions that translate in time and whose length and magnitude were scaled as a function of the frequency. Morani et al. [11] proposed the use of a suitable band-pass filters-bank to capture the sinusoidal components in the signal. The benefit of using this method is that it needs only limited knowledge of the process under control and can be used in real-time to detect oscillations; however, the method can be very sensitive to noise.

In this paper, we present a frequency domain method for the detection of oscillation. Our method relies on representing the time-domain data into frequency domain using a Fourier basis over a frequency range that represents off-nominal behavior for the system. Once in frequency domain, the dominant frequencies can be analyzed to detect and even to mitigate oscillations. A key benefit of using the method presented here arises from the use of recursive Fourier transform [12], which ensures that no explicit storage of a window of measured data is required; rather only a fixed dimension vector of the Fourier coefficients over the desired frequency range needs to be stored. These qualities of the presented method are conducive to real-time implementation onboard Unmanned Aerial Systems (UAS), where computational resources may be restricted. One interesting application of this method is to use it in a Monte-Carlo simulation to determine the thresholds on adaptation gains within which no undesirable oscillations are caused. Another application of this tool is the development of an automatic gain-changer, which changes the adaptation gain over the flight envelope so as to maintain an optimum amount of oscillation in the system without triggering an oscillation. This is of particular significance because the gain changer will allow the system to adapt to reference dynamics as quickly as possible without causing undesirable oscillations.

We begin by describing the details of discrete recursive implementation of Fourier transform. The feasibility of this method is then assessed for the detection of a high gain-control-induced oscillation on an exemplary adaptive control problem. Finally, the presented method is used to detect the onset of angle-of-attack oscillation on the data from the Georgia Tech (GT) Twinstar UAS recorded during an enforced 50% loss of right wing, and to detect oscillations due to injected time delay.

## II. Frequency Domain Detection of Oscillation

The Fourier transform of an arbitrary signal  $x(t)$  is given by

$$F[x(t)] \equiv \hat{x}(\omega) \equiv \int_{-\infty}^{+\infty} x(t)e^{-j\omega t} dt \quad (1)$$

The signals of interest in this study are collected via a data sampling system and so the discrete version of the Fourier transform is required. The discrete Fourier transform is given by

$$X(\omega) \equiv \sum_{i=0}^{N-1} x_i(t_i) e^{-j\omega t_i} \quad (2)$$

The Euler approximation of the Fourier transform in Eq. (1) is given by

$$\tilde{x}(\omega) \approx X(\omega) \Delta t \quad (3)$$

This approximation is suitable if the sampling rate is much higher than any of the frequencies of interest. This is assumed to be the case in this paper. The discrete version of the Fourier transform can be propagated in a recursive manner as follows [12]:

$$X_k(\omega) = X_{k-1}(\omega) + x(t_k) e^{-j\omega k \Delta t} \quad (4)$$

The recursive propagation of the Fourier transform greatly facilitates real-time implementation as the matrix  $X_k$  is the only matrix that needs to be stored in the system memory. For a frequency range of interest, ( $[1, \dots, m]$ ), the matrix representing the Fourier basis of the time-domain data is given by

$$\tilde{X}(\omega) = \begin{bmatrix} \tilde{x}(1) \\ \tilde{x}(2) \\ \vdots \\ \tilde{x}(m) \end{bmatrix} \quad (5)$$

Using the preceding equations, the frequency content of the measured data can be approximated by a finite Fourier basis. For the detection of oscillation, we simply restrict our attention to a particular frequency range of interest that characterizes the off-nominal behavior of the system. This is similar to projecting the data over a finite subset of the Fourier basis. The discrete Fourier transform (DFT) of a signal at a particular time instant ( $t = T$ ) contains the frequency information in the signal from time  $t = 0$  to  $t = T$ . This memory-like property can cause past oscillations to mistakenly trigger the detection algorithm. We handle this issue by using a windowed DFT given subsequently.

$$\Delta X(\omega)_{t=T} = X(\omega)_{t=T} - X(\omega)_{t=T-k} \quad (6)$$

The difference between the DFT at  $t = T$  and the DFT at  $t = T - k$  is a measure of the frequency content in the signal in the time window between  $T$  and  $T - k$ . In this way, the information about the magnitude and frequency of oscillations over a window of data can be stored in a single variable. To detect oscillations, we monitor the norm of this windowed Fourier transform. If the norm exceeds a prespecified threshold value, it indicates the presence of excessive activity in that frequency range, which is considered as a strong indication of undesirable oscillation and a flag is raised. Let  $x \in \{0, 1\}$  denote the output of the flag, with  $x = 1$  if the norm exceeds the threshold value, and  $x = 0$  otherwise. This flag is discrete, and would tend to rapidly switch between 1 and 0 through transient phases when oscillations are building up or waning down. Such rapid switching could lead to undesirable situations if the flag value is used as an input to another onboard algorithm, such as a gain-scheduler. To smoothen the flag value, the flag is passed through a discrete implementation of a first-order low-pass filter. Note that other methods, such as discrete averaging, or monitoring whether the flag is on for a predefined time over a window of stored flag values, can also be used to smoothen the output. However, these methods may require that the flag outputs be stored over a window of data; a low-pass filter, on the other hand, achieves similar results without requiring explicit storage and has guaranteed transient performance. Let  $y$  denote the filter state; then the low-pass filter has the form

$$\dot{y}(t) = \frac{-(y(t) - x(t))}{\tau} \quad (7)$$

Equation (7) represents a first-order low-pass filter, with a continuous output  $y$  constrained between 0 and 1. Here, the low-pass filter serves two functions. First, it smoothenes the output of the algorithm by smoothing out the chance

outlying flags. Second, it provided a metric for determining the confidence of the algorithm in detecting oscillations. Particularly, the numerical value of the output of the low-pass filter ( $y$ ) can be thought of as an indicator of the confidence of the method in the detection of oscillations. Furthermore, the time rate of change of  $y$  can be thought of as an indicator of whether the oscillations are increasing or diminishing. Therefore, the time constant  $\tau$  becomes a design parameter for this method. A larger time constant results in a smoother output, and is desirable for detecting the presence of sustained oscillations, whereas a smaller time constant increases the sensitivity of the algorithm, and is desirable for detecting the presence of transient oscillations. Along with the time constant  $\tau$ , the design parameters for this method are the frequency band of interest to be monitored, the threshold value, and the window size  $k$ . The frequency band and the threshold value should be physically motivated to characterize the off-nominal behavior of the system. The window size, along with the time constant, determines the sensitivity of the algorithm. A smaller window size results in the algorithm considering only recent data for oscillation detection, whereas a larger window size ensures that the effect of past data is also included. In practice, the size of the window should be chosen to be at least as large as the period of the lowest frequency in the frequency band to be monitored. Instead of windowed Fourier transforms, it is also possible to use a forgetting factor to discount old data [12].

### III. Detection of Oscillation from an Exemplary Adaptive Control Problem

To assess the feasibility of the presented approach, we present an exemplary problem of detection of bursting phenomena [2] in an adaptive controller simulation. Let  $x$  denote the state vector,  $u$  denote the control input, and consider the problem of controlling the following system:

$$\dot{x}(t) = 3x(t) + 2u(t) + w_d(t) \quad (8)$$

$$y(t) = x(t) + w_s(t) \quad (9)$$

Here  $y$  denotes the measurement vector. A linear reference model is chosen to characterize the response of the system. Let  $x_r$  denote the states of the reference model, and  $r(t)$  denote a desired reference signal that is treated as an input to the reference model given by

$$\dot{x}_r(t) = -2x_r(t) + 3r(t) \quad (10)$$

The tracking error can be defined as  $e(t) = x_r(t) - x(t)$ . A stable adaptive controller for this problem can be found by using the Lyapunov theory [2,13,14], and is given as

$$u(t) = k_x(t)e(t) + k_r(t)r(t) \quad (11)$$

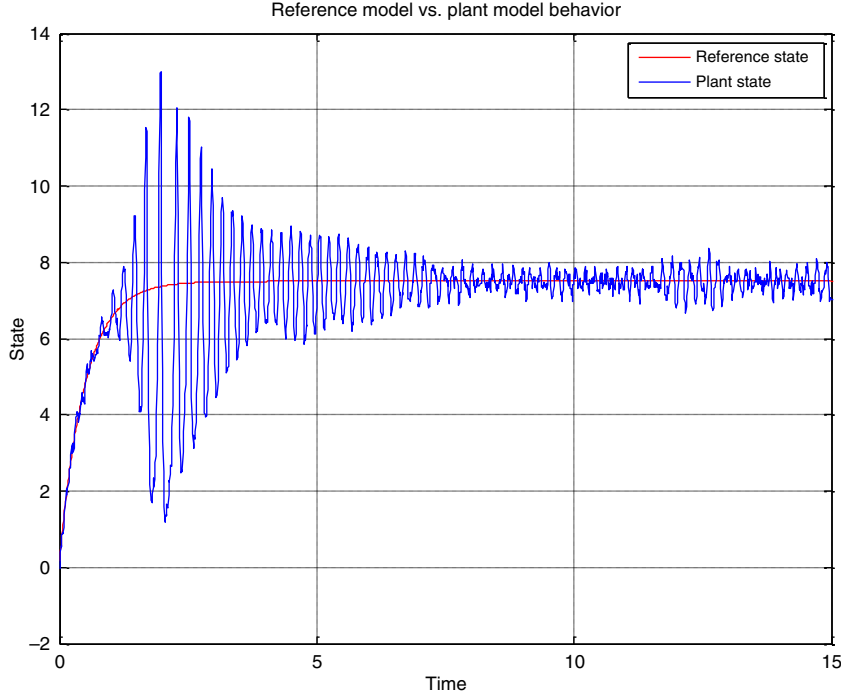
The adaptive weights are updated by the following well-known learning law [2,13,14]:

$$\dot{k}_x(t) = -\gamma_x x(t)e(t) \text{sign}(B) \quad (12)$$

$$\dot{k}_r(t) = -\gamma_r r(t)e(t) \text{sign}(B) \quad (13)$$

High learning rates ( $\gamma_x = 10$ ,  $\gamma_r = 0.5$ ) are used in order to simulate the bursting phenomena [2]. Bursting is a sudden onset of a high-frequency and high-amplitude oscillation in the system state as a result of high adaptation gains. Early detection of the onset of bursting can be used to prevent damage to the system and to mitigate the oscillations. To detect the onset of bursting, we monitor the tracking error  $e(t)$  over a frequency range of 2–6 Hz using the windowed Fourier transform method discussed in the preceding section. The time step used for the simulation is 0.01 s. The threshold value and the window size are determined to be 64 and 0.36 s, respectively, by using the nominal transient response characteristics of the reference model. Particularly, the threshold value was obtained by taking the mean of the recorded norm at each time step of the tracking error windowed Fourier transform for a nominal step input until steady-state is reached. Alternatively, the threshold value can also be determined using the known frequency response characteristics of the reference model.

Zero-mean Gaussian white noise with a standard deviation of 0.1 was added to the system to simulate the effect of sensor noise ( $w_s$ ) in the measurements. A significant source of state disturbance ( $w_d$ ) that many mechanical



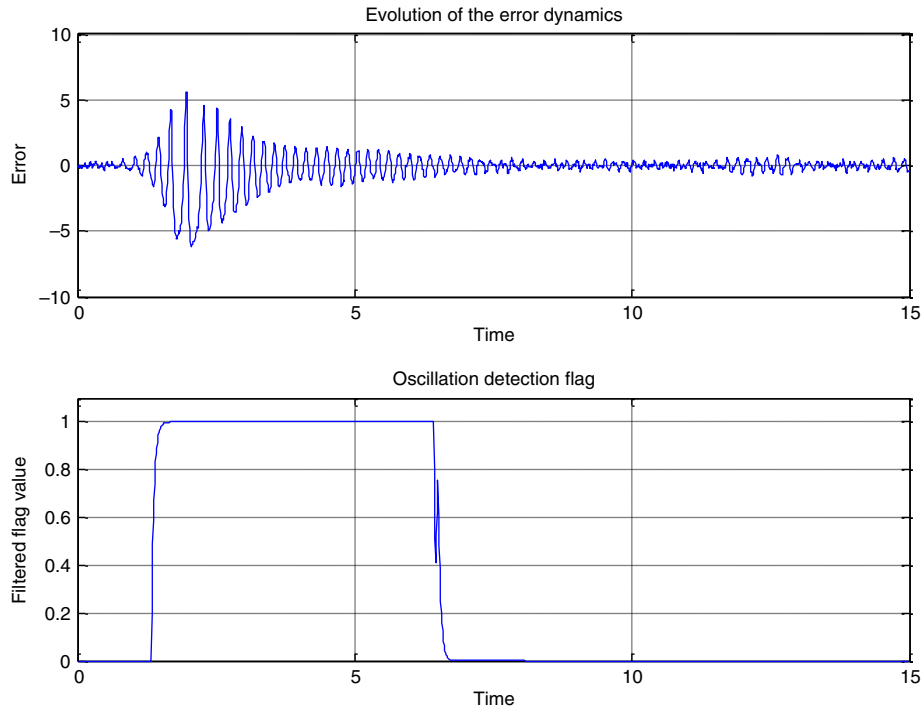
**Fig. 1** The performance of the adaptive controller. Note that bursting, characterized by high-frequency oscillations, occurs as the controller tracks a reference state.

systems are subject to is the vibration caused due to loose mechanical parts and rotating elements. We model these disturbances as low-amplitude high-frequency sinusoidal oscillations:  $w_d(t) = 0.1 \sin(20\pi t)$ . If such oscillations are considered nominal, then they should not be detected by the oscillation-detection algorithm.

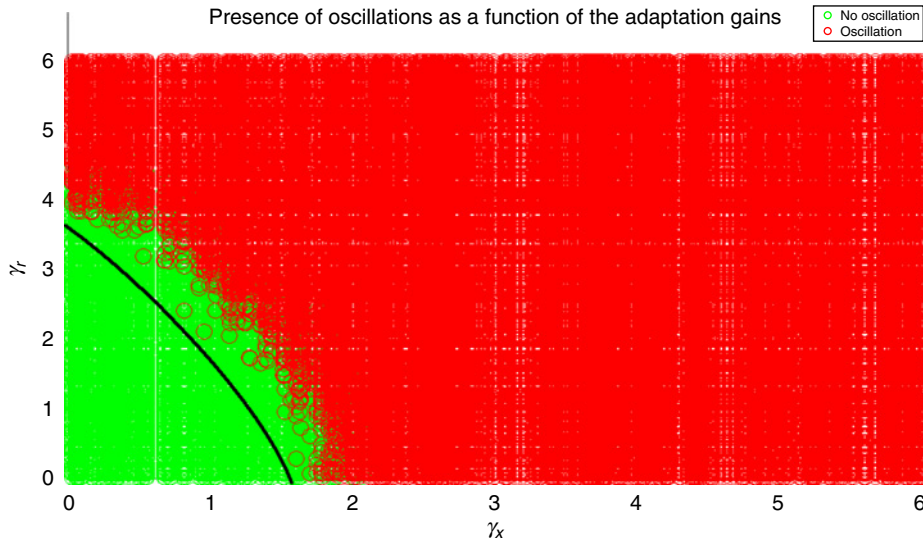
Figure 1 shows the performance of the adaptive controller for a nominal linear system. The controller attempts to track a constant reference command of  $r(t) = 5$ . It can be seen that the controller tracks the command with little error until about 1.3 s. Between 1.3 and 5.8 s, the system state exhibits the bursting phenomena characterized by a high-frequency and high-amplitude oscillation about the reference model state.

Figure 2 shows the performance of the detection algorithm. A flag that is passed through a discrete low-pass filter with a time constant of 0.05 s is plotted on the bottom part of the figure. A filtered flag value of 1 indicates high confidence in the presence of oscillations, whereas a value of 0 indicates that no oscillations over the frequency range of interest are present. The algorithm is able to detect the onset of bursting early on and drives the oscillation-detection flag to 1. Furthermore, the algorithm also detects the end of the bursting phenomena and drives the oscillation-detection flag back to 0 as the system resumes nominal behavior in the presence of noise.

The ability to detect oscillations using the frequency domain method discussed in the preceding sections has several further applications. One extension is to use this method in feedback control loops to detect and to possibly mitigate the oscillations. Particularly, the information on the frequency and magnitude of the oscillations obtained from the algorithm can be used to drive an automatic gain-changing system. The presented method can also be used to determine a range of adaptation gains ( $\gamma_x, \gamma_r$ ) that ensure the system oscillations are contained in a predefined frequency range through Monte-Carlo simulations. Figure 3 indicates the presence of oscillations in the system of Eq. (8) as a function of the adaptation gains. For the results presented in this paper, a Monte-Carlo like simulation was performed for 300 uniformly distributed samples of the gain values between 0 and 6. The black line in that figure depicts an estimate of the gain boundaries which ensure the system operates within a predefined frequency range in the presence of disturbances. Through such analysis, an a priori bound on the adaptation gains can be found.



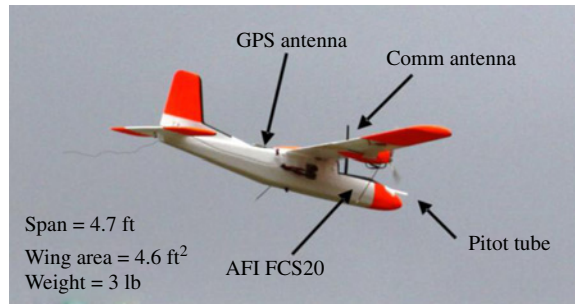
**Fig. 2** Detection of onset of bursting. The presented algorithm quickly detects the buildup of oscillations due to the bursting phenomena. The algorithm also quickly detects the waning of oscillations as bursting subsides.



**Fig. 3** The presence of oscillations for different gain values using the oscillation-detection tool presented in this paper. Note that the adaptive gains to the left of the black curve ensure that the system operates in a predefined frequency range.

#### IV. Application to Vehicle Health Monitoring for the GT Twinstar UAS

The GT Twinstar shown in Fig. 4 is a fixed Wing UAS. It is a foam-built, twin-engine aircraft that is equipped with an integrated off-the-shelf autopilot system (Adaptive Flight FCS 20<sup>©</sup>). Georgia Tech Twinstar has been specifically



**Fig. 4** GT Twinstar fixed wing UAV. The Twinstar is a twin-engine airplane that has been designed and outfitted specifically for a fault-tolerant control work.



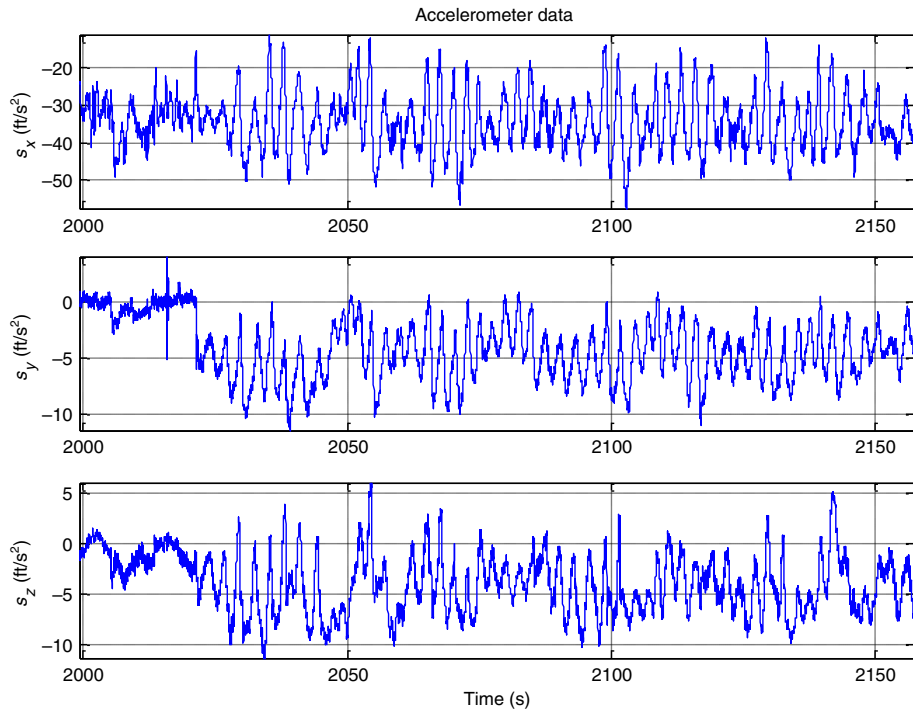
**Fig. 5** GT Twinstar in autonomous flight after jettisoning 50% of its right wing in autonomous flight to simulate a severe structural damage.

developed for a fault-tolerant control system work [15–17]. It comes equipped with an ability to inject actuator time delays and simulate actuator failures; furthermore, GT Twinstar is capable of jettisoning 50% right (starboard) wing while in autonomous flight. In this section, we use recorded data from GT Twinstar for demonstrating the feasibility of the developed approach for detecting oscillations. These recorded data include controlled system response to 50% loss of right wing [17], and to injected actuator time delay [18]. For both the applications described in the following sections, the threshold value was obtained in the following manner: using data sets that had been collected previously when the aircraft was performing System-ID maneuvers [16], the windowed Fourier transform of the states was monitored. The norm of the windowed Fourier transform was calculated at each time step and its mean value was used as the threshold for detecting oscillations in the system.

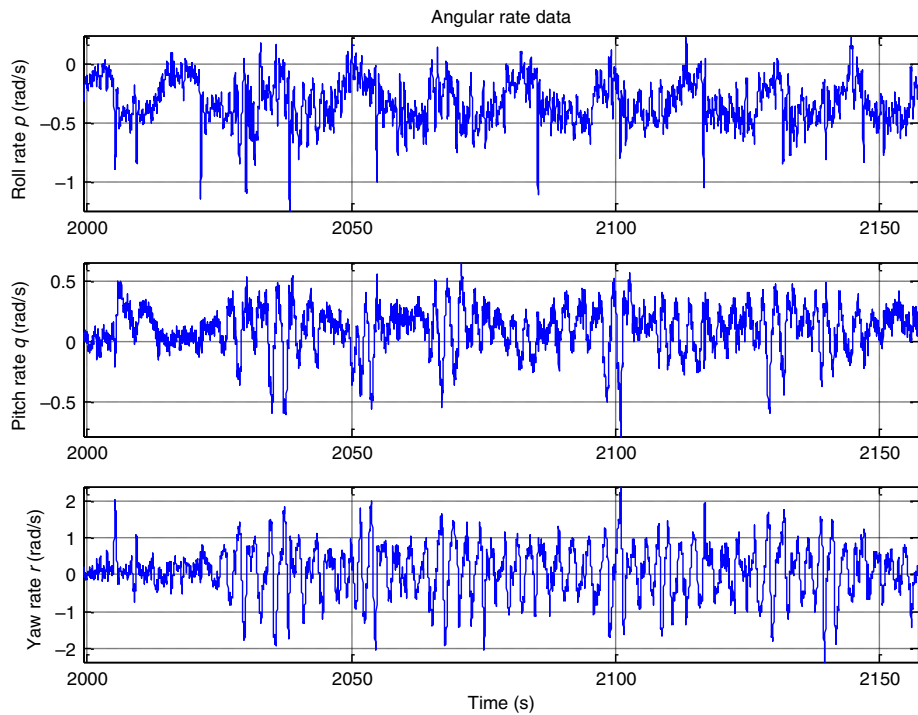
#### **A. Detection of Oscillations in the Angle-of-Attack due to Asymmetric Loss of Lifting Surface**

Figure 5 shows the GT Twinstar in flight with 50% of its right (starboard) wing lost as the aircraft performs an autonomous holding pattern about a given waypoint. Figure 6 shows a slice of recorded accelerometer measurements onboard the GT Twinstar. A sharp spike in the  $y$ -axis accelerometer at around 16 s indicates the engagement of the jettisoning mechanism. The wing physically separates from the vehicle approximately 4 s later, at around 22 s into the recorded data. The resulting significant change in the system dynamics is characterized by an oscillation primarily in the angle-of-attack and roll rate. Figure 7 shows the recorded angular rate measurements onboard GT Twinstar. A video of the Twinstar as it jettisons 50% of its right wing in autonomous flight can be found by at this link. The video corresponds to the flight test data presented in this paper.

Figure 8 shows the performance of the presented oscillation-detection algorithm. The algorithm monitors a frequency range between 2 and 6 Hz based on physical considerations and a power spectral density analysis of recorded data in nominal flight conditions. Nominal flight data were used to determine the threshold value used for setting oscillation-detection flag to 1. The flag is passed through a low-pass filter (Eq. (7)) with a time constant of

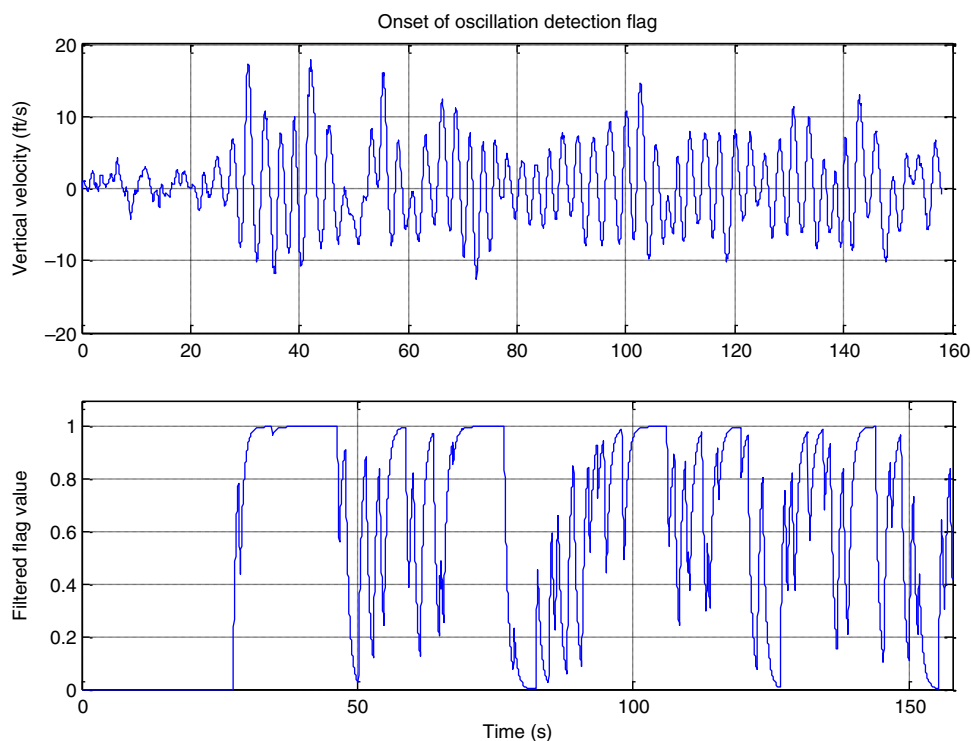


**Fig. 6** Recorded accelerometer measurements. Note that the wing separates around 2020 s from the flight. The separation causes oscillations in the states as depicted by the sensor measurements.



**Fig. 7** Recorded angular-rate measurements.



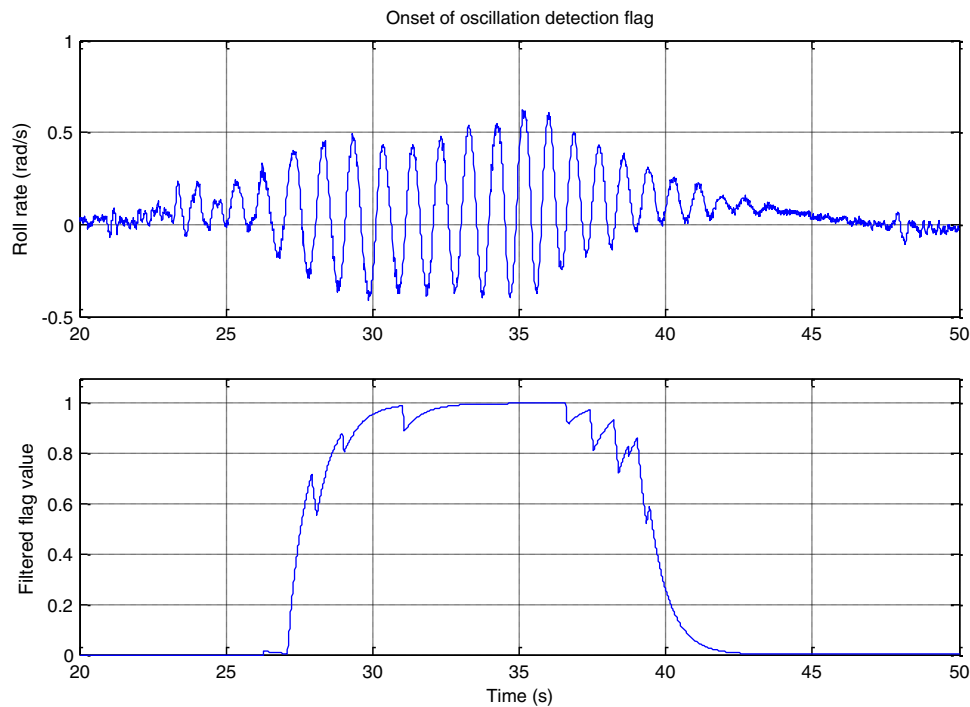


**Fig. 8** Detection of oscillations on the Twinstar UAS due to asymmetric loss of lifting surface. Note that the presented oscillation-detection algorithm is quick in detecting the induced oscillations. Furthermore, the algorithm has sufficient sensitivity to detect the changes in the magnitude and the frequency of the oscillations as the airplane tracks a circular holding pattern.

0.67 s implemented discretely with an update rate of 50 Hz corresponding to the rate at which the data were recorded. The output of the low-pass filter is plotted on the bottom part of the figure. In that plot, a value of 1 indicates high confidence in the presence of sustained oscillations, whereas a value of 0 indicates that no oscillations over the frequency range characterizing off-nominal behavior are present. The algorithm is able to detect the onset of oscillations immediately after the partial loss of wing and drives the output of the low-pass filter to 1. The response of the system is characterized by intermittent oscillations after around 50 s into the recorded data and this is also reflected by the output of the low-pass filter.

### B. Detection of Oscillations due to Injected Time Delay

The presence of time delay can lead to sustained oscillations and instability in adaptive controllers. To counter this, Calise et al. [18] have developed the adaptive loop recovery (ALR) method capable of recovering the phase margin of the baseline nonadaptive design. In this section, we demonstrate the effectiveness of the presented method in detecting oscillations in the control system due to injected time delay on the GT Twinstar UAS. Figure 9 shows the performance of the presented algorithm in detecting oscillations in the roll rate due to the injected time delay of about 100 ms. Nominal flight data were used to determine the threshold value used for setting the oscillation-detection flag to 1. The flag data are passed through a low-pass filter with a time constant of 0.67 s implemented discretely with an update rate of 100 Hz corresponding to the rate at which the data were recorded. The algorithm detects the oscillation in the roll rate due to injected time delay at about 27 s. As the ALR gains are gradually increased starting from around 36 s, a gradual reduction in the oscillation is seen; reflected by a downward trend in the filtered flag value. The flag eventually settles down to zero once the oscillations due to time delay are effectively mitigated by ALR.



**Fig. 9** Detection of oscillation due to the injection of time delay using the presented algorithm. Note that the algorithm quickly picks up the buildup and waning of oscillations in roll rate.

## V. Conclusion

A frequency domain method of detecting oscillations was presented. The presented method represents time-domain data in a frequency domain Fourier basis over a range of frequency that indicates off-nominal behavior for the system. This method is both computationally efficient and requires limited memory; therefore, it was found to be effective for real-time implementation. We presented results showing the feasibility of using the proposed method as a metric for the detection of the onset of bursting phenomenon in an exemplary adaptive control problem. The method was used to determine a priori bounds on the adaptation gains through Monte-Carlo simulations. The presented method was also used to detect structural failure and time-delay-induced oscillations in recorded flight data from the GT Twinstar UAS. A unique benefit of using this method is that it enumerates magnitude and frequency information about the oscillations in a single variable. Hence, this method holds great potential for use in the mitigation of oscillations in control loops.

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