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FLIGHT DATA CLASSIFIER FOR EFFECTIVE AIRCRAFT PERFORMANCE ANALYSIS

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Abstract

A classifier, with which stable flight represented by steady cruise is detected from flight data of aircraft, is proposed. It enables us to utilize not only dedicated but also ordinary flight data for estimations of flight performance such as aerodynamic parameters. The classifier firstly performs extracting instantaneous time-frequency information from flight data with a filter bank. Then, determining whether stable conditions are satisfied based on differences of imitated slopes is conducted. The slopes are calculated with changes of the time-frequency information, which enables the stable conditions to be configured intuitively and makes filtering out outliers easier. The proposed classifier is evaluated with real flight data, and its effectiveness is proved by computing lift coefficient with the data.

1 Introduction

Flight data consisting of time histories of aircraft states such as attitude, control surface deflections, is valuable to analyze. Especially, it is important to estimate performance by using the data, because the estimated performance is used for verification of prediction at design phase. Moreover, quantitative performance represented by aerodynamic parameters and stability derivatives must be estimated to compare with results of wind tunnel tests or computational fluid dynamics calculations. These estimations are well established to use system identification framework, however, the framework has an essential guideline for application. It is summarized that accuracy of the estimated results is quite dependent on quality of the flight data used for the estimations. Thus, dedicated flight tests, in which preferred conditions such as calm wind are met, have been conducted to gather appropriate flight data for the estimations. In addition, not only standard but also special maneuvers, which excite specific modes of flight dynamics such as vertical short-period motion of fixed-wing aircraft, are performed in the tests. Furthermore, data compatibility checks, which remove undesirable part by measuring kinematic correlation between control inputs and responses, are applied to obtained data.

Indeed the dedicated flight tests are requisite, however, all flight should be utilized for the estimations. This is because longer flight data is suitable to obtain more plausible results from statistics point of view, and number of the dedicated flight tests is limited. Moreover, monitoring changes of the flight performance, which contributes to early detection of aircraft failure, will be possible if part of the ordinary logged flight data can be used for the estimations.

Here, there are questions; which parts of flight data are selected, and how to extract them automatically from massive flight data. In this study, steady flight in cruise, ascend, and descend phases, is selected as “stable flight”. This is because the stable flight is required to estimate static flight performance represented by lift and drag coefficients. In addition, this selection introduces another good point. The unselected part also will be utilized for the estimation of dynamic characteristics such as stability derivatives.

For effective extraction of the stable flight, a new classifier is proposed. This classifier detects changes of flight data in terms of period, and selects the stable flight parts in which the changes are acceptable. To focus the changes is effective for the extraction, because stable flight mostly occupies ordinary flight. Moreover, it is quite important to consider not only magnitude but also period of the changes. This is because parts of data in which short-term strong changes derived mainly from maneuver and gust are observed should be dismissed, while long-term gradual changes such as constant increase of altitude in ascend phase should be accepted. In order to observe both magnitude and period, the proposed classifier utilizes time-frequency information converted from time-series flight data by a filter bank. The filter bank is configured with techniques of multiresolution analysis (MRA) [1] derived from discrete wavelet transform (DWT) to calculate the information effectively. In addition, imitated slopes calculated with the time-frequency information are introduced to make the proposed method customize easily.

In the following, the contribution of this work is defined with related studies in section 2. Then, the proposed classifier details are explained in section 3. The proposed classifier is evaluated and its results are described in section 4. Finally, in section 5, this study is concluded.

2 Related studies and contribution of this study

The flight data analysis in this study is correlated to researches of time-series data analysis. Thus, the contribution of this study is clarified with summaries of the previous researches.

The time-series data analysis has been studied with its many applications such as analyses of stock prices, brain wave, and earthquake. One of major frameworks of these existing studies is similarity search, whose goal is to find similar parts corresponding to a given query from time series data. The general procedure of the search is firstly making indexes of the data and storing the indexes and the original data in a database. Then, the query is also converted to a corresponding index with the same way applied to the data, and indirect comparison between the data and query, then, extraction of candidates for the similar parts are performed with their indexes. Finally, results are obtained by refining the candidates with direct comparison between their original data and query.

Index generation techniques and special database structures have been actively researched in the above procedure for processing larger data and answering queries more quickly. For index generation, feature extraction methods represented by fast Fourier transform (FFT), discrete wavelet transform (DWT), singular value decomposition (SVD), and landmark extraction are well utilized [2, 3, 4, 5, 6]. Every method is arranged to reduce dimension of the data and generate appropriate indexes, which do not invoke any false dismissal at the cost of acceptance of certain false alarm when the indirect comparison is performed. For instance, several coefficients of Fourier transform results of the data are selected as the indexes.

For database, multi dimensional and hierarchical structures such as *R*-tree [7] and CS-index [8] are utilized. These special structures make the indirect comparisons quicker by arranging comparison order. The comparisons are performed from coarse to fine levels, which implies that if a coarse level comparison fails, then, the remaining finer ones are pruned.

For this study, the existing index generation techniques seem to be useful. However, according to Keogh [9], usability of the existing techniques is limited. It indicates that with just few types of data, these techniques were evaluated in order to prove their performance. In the worth case, when they are applied to other data which are not assumed, their performance was inferior to the simplest and most redundant technique using Euclidean distance. This means an appropriate method must be used based on characteristics of application data. Therefore, the dedicated method for the flight data analysis will be proposed in this study.

3 Proposed method

The proposed method is mainly characterized by using time-frequency information converted from time-series flight data. The information is continuously obtained with a filter bank configured by using MRA techniques. To observe the information, long- and short-term changes, which are mostly suspected to be intended and unintended changes, respectively, can be distinguished. This is because the information represents how strong signal is in certain frequency band and period. Moreover, the proposed method utilizes the information to classify the data into the stable flight by finding parts in which middle-term changes are sufficiently identical to long-term changes. The fundamental idea to select not short- but middle-term changes is lower frequency is more deteriorated by measurement noise, which are mostly localized in higher frequency band.

In the following, MRA and the filter bank will be briefly explained, and then, the procedure of the proposed method is described. The characteristics of the method can be determined with parameters, whose tuning techniques are also described.

3.1 Multiresolution analysis and filter bank

Time-frequency information is calculated by several ways such as short-time Fourier transform (STFT) and DWT. Especially, MRA is an effective way to apply DWT to time-series data. Figure 1 shows a part of MRA calculation procedure using Haar wavelet, the simplest one. This Haar MRA consists of blocks which have identical structure and are connected serially. In one block, it performs calculation of difference and mean of two adjacent samples, then, downsamples them by two. The down-sampled mean value is propagated to a next block. An example of the Haar MRA applied to a chirp waveform whose periodical changes are more frequent as time passes is shown in Fig. 2, from which it is exactly confirmed that frequency component of the waveform is changed.

The MRA using Haar wavelet is modified in

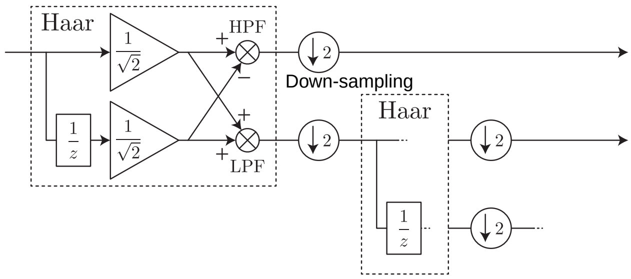

Fig. 1 Calculation procedure of multiresolution analysis (MRA) using Haar wavelet

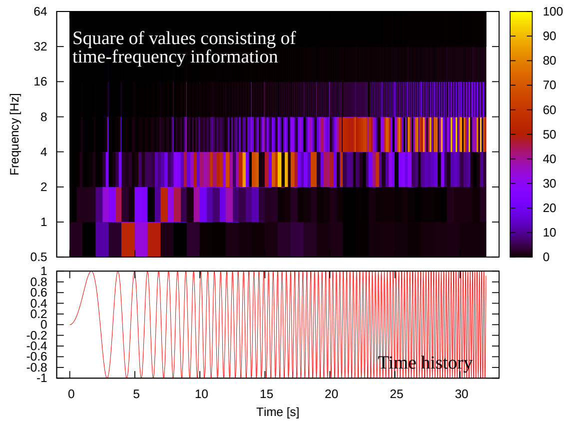

Fig. 2 Time history of a linear chirp signal (bottom) and its MRA results (top). The MRA results are shown with square of values consisting of time-frequency information, which represents signal strength.

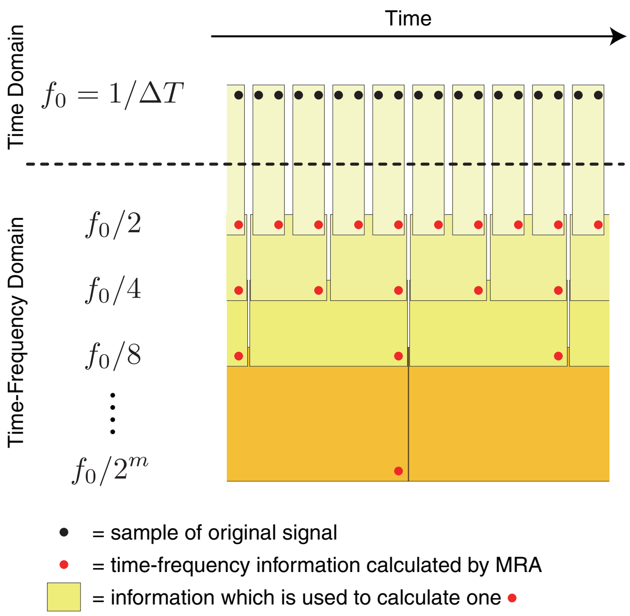

Fig. 3 Conceptual timing chart chart of MRA using Haar wavelet

this study. The information obtained with the original MRA is scattered in terms of time shown in Fig. 3 because of down-sampling. Generally, it is not problematic because the transformed time-frequency information does not drop any content that the original time-series data has due to orthonormal feature of Haar wavelet. However, for the classification of this study, redundant time-frequency information which is instantaneously available at any time when time-series data is sampled is useful. Thus, replacement of down-sampling to delaying is introduced and the filter bank shown in Fig. 4 is utilized in this study. The filter bank contains additional delay in order to compensate for delay contained in the Haar blocks and to output the instantaneous information. Consequently, the filter bank generates instantaneous information like shown in Fig. 5. The red arrows in the figure correspond to the additional delay.

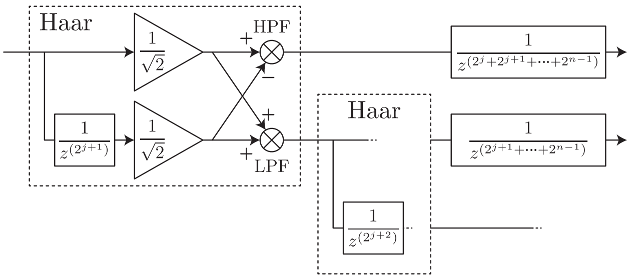

Fig. 4 Calculation procedure of the filter bank of the proposed method

Figure 6 shows instantaneous time-frequency information of the same chirp waveform in Fig. 2 obtained with the filter bank. It is the same as Fig. 2 that higher frequency components gradually oscillate in larger amplitude.

3.2 Proposed method overview

Figure 7 illustrates the overview of the proposed method. The method receives time-series data as inputs at the left side in the figure, and returns classified results weather the data satisfies conditions of the stable flight or not as outputs as the right side in the figure. At the front stage, the filter bank explained in the previous subsection is applied to obtain instantaneous time-frequency information.

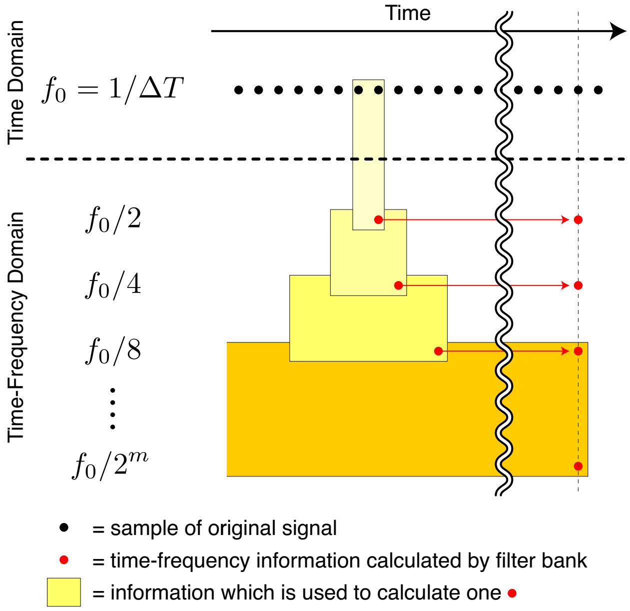

Fig. 5 Conceptual timing chart chart of the filter bank of the proposed method. By sliding the area to be used for calculation, instantaneous time-frequency information is obtained.

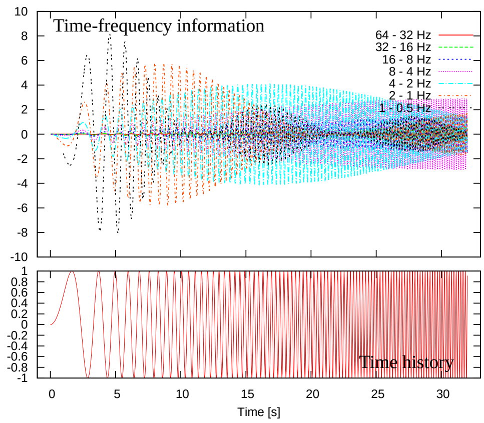

Fig. 6 Time history of the same linear chirp signal (bottom) and its instantaneous time-frequency information generated with the filter bank results (top)

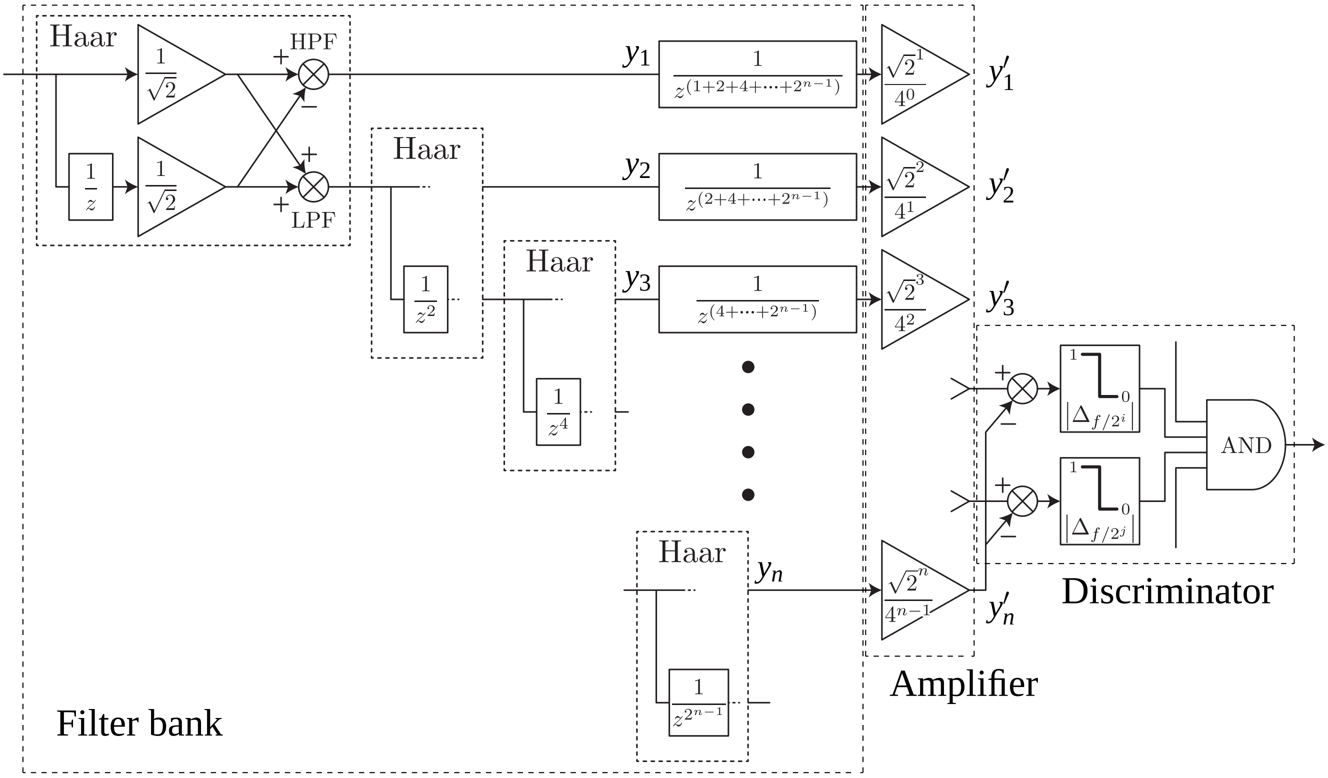

Fig. 7 Proposed classifier

Then, amplifiers to regulate magnitude of values consisting of time-frequency information exist. The gains of the amplifiers are selected for the amplified values to be compared directly among any frequency band. Here, a differential output of i-th Haar block y_i is calculated as

$$y_i = \frac{\sum_{j=k}^{k+2^{i-1}-1} a_j - \sum_{j=k+2^{i-1}}^{k+2^i-1} a_j}{\sqrt{2}^i}, \tag{1}$$

where a_j is j-th sample of time-series data. Then, $\frac{\sqrt{2}^i}{4^{i-1}}$ is multiplied as the gain, the amplified value y'_i is

$$\begin{aligned} y'_i = \frac{\sqrt{2}^i}{4^{i-1}} y_i &= \frac{\frac{1}{2^{i-1}}\sum^{2^{i-1}} a_k - \frac{1}{2^{i-1}}\sum^{2^{i-1}} a_{k+2^{i-1}}}{2^{i-1}} \\ &\equiv \frac{\bar{a}_{2^{i-1},k} - \bar{a}_{2^{i-1},k+2^{i-1}}}{2^{i-1}}, \end{aligned} \tag{2}$$

where $\bar{a}_{2^{i-1},k}$ represents a mean value from k-th to $\left(k+2^{n-1}-1\right)$-th samples. The distance between $\bar{a}_{2^{i-1},k}$ and $\bar{a}_{2^{i-1},k+2^{i-1}}$ is 2^{i-1} samples, thus, the amplified value y'_i imitates (negative) slopes in time domain.

At the last stage, a discriminator checks whether the stable flight conditions are satisfied or not. The discriminator computes differences between long- and middle-term changes based on the imitated slopes. When the slope differences are smaller than predefined thresholds Δ, the discriminator alarms that the stable flight is achieved in terms of the input time-series data.

3.3 Parameter tuning

The proposed method has three kinds of tunable parameters; lowest frequency of the filter bank, frequency band whose imitated slopes are compared, and thresholds of the discriminator. The lowest frequency of the filter bank is determined based on minimum period of intended changes. For example, intended changes of altitude are suspected to endure for 32 seconds at least, the lowest frequency of the filter bank is $1/32$ Hz. In other words, if the sampling period of altitude is 8 Hz, this corresponds to that $8\,(=\log_2(32\,[\mathrm{s}]/(1/8\,[1/\mathrm{s}])))$ of the Haar blocks are cascaded in the filter bank.

The frequency bands whose imitated slopes are compared with ones of the lowest frequency band are also determined empirically. To use the altitude example, the imitated slopes generated from the 6th and 7th Haar blocks will be observed. This corresponds to middle-term changes whose periods are 4 to 16 seconds.

Finally, the thresholds are easily defined by using the fact that the amplified values imitate the slopes in time-domain. With the altitude example, it is reasonable to determine flight is not stable when absolute deviation of altitude rate between middle- and long-term changes is larger than 100 fpm. Combined with the frequency bands previously determined, in this example, the thresholds will be $\left|\Delta_{f/2^6}\right| = \left|\Delta_{f/2^7}\right| = 100/(60\,[\mathrm{sec}] * 8\,[1/\mathrm{s}])$ feet per sample.

4 Evaluation and results

As evaluations of the proposed method, ordinal flight data of experimental aircraft "Hisho" [10] owned by Japan Aerospace Exploration Agency (JAXA) is used. "Hisho" is modified aircraft whose original is Cessna Model 680 fixed-wing aircraft powered by two turbofan engines. The data consists of time-series data recorded with various instruments represented by ineartial measurement unit (IMU), air data computer (ADC), and engine controller known as FADEC. The length of the flight data to be analyzed is approximately one hour, and the data is aligned for its sampling frequency to be 10 Hz.

To extract the stable flight from the flight data, among various measured items, the following four time histories are focused; altitude h, true airspeed V_{TAS}, pitch angle θ, and roll angle ϕ. The former two items are obtained with ADC, while the latter two items are measured with IMU. Each item will be monitored by each dedicated classifier, and final classification results will be obtained by performing "AND" operation for the outputs of these four classifiers. In addition, minimum duration of the stable flight is defined as 15 seconds, which means that even if the data is classified as stable, and when length of the data is shorter than 15 seconds, the data is forcely recognized as not stable. The tunable parameters of the classifiers are configured empirically based on Sec. 3.3, and are summarized in Table 1. Every filter bank of the classifiers for the target items has eight Haar blocks, which is equivalent to 10/256 Hz of its lowest frequency, that is, dividing 10 Hz of the sampling frequency by the 8th power of 2. Frequency bands whose imitated slopes are compared are also configured with a common band from 10/32 to 10/64 Hz, which corresponds to monitoring outputs of the 6th Haar block in the discriminators.

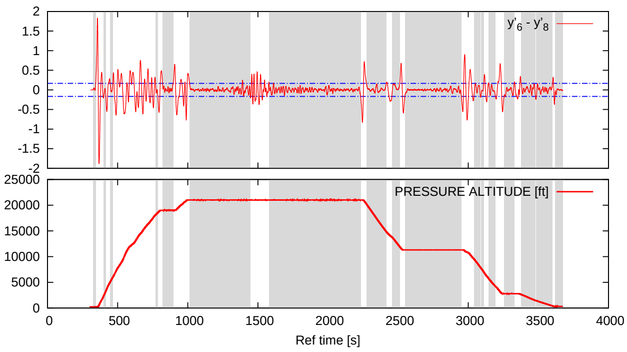

Fig. 8 Altitude

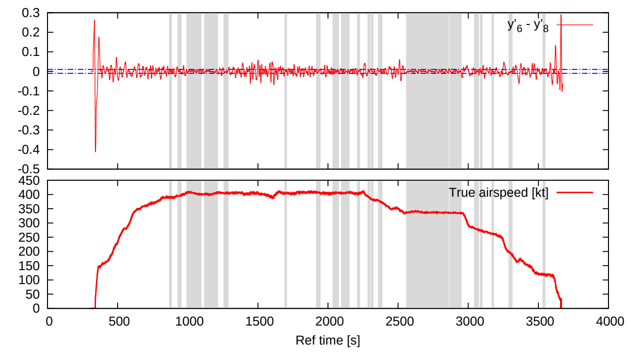

Fig. 9 True airspeed

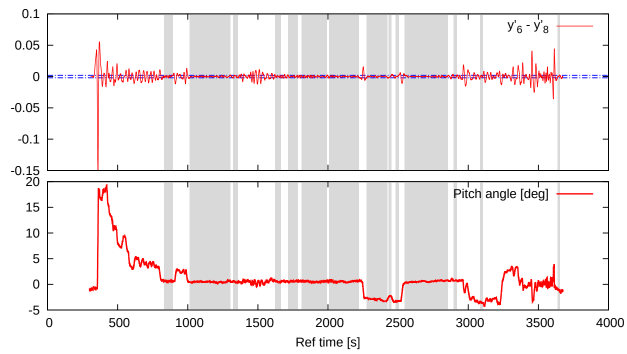

Fig. 10 Pitch angle

Figures 8-11 are the classified results of the focused items, i.e., altitude, true airspeed, pitch

Table 1 Parameters of the classifier

Item	Symbol	Lowest frequency (Haar blocks)	Compared frequency band and thresholds
Altitude	h	10/256 [Hz] (8)	$\lvert\Delta_{10/64}\rvert = 100$[fpm] $= 0.167$[feet per sample]
True airspeed	V_{TAS}	10/256 [Hz] (8)	$\lvert\Delta_{10/64}\rvert = 0.1$[kt per sec] $= 0.01$[knots per sample]
Pitch angle	θ	10/256 [Hz] (8)	$\lvert\Delta_{10/64}\rvert = 0.02$[dps] $= 0.002$[degrees per sample]
Roll angle	ϕ	10/256 [Hz] (8)	$\lvert\Delta_{10/64}\rvert = 0.1$[dps] $= 0.01$[degrees per sample]

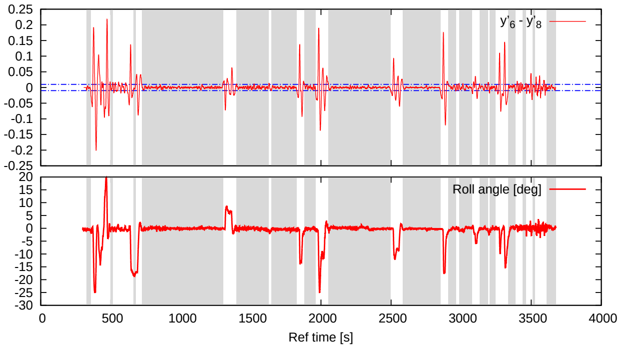

Fig. 11 Roll angle

and roll angles, respectively. Each figure shows time history of raw values and inputs to the discriminator in bottom and top subfigures, respectively. The shadowed area in the figures denotes the data recognized as stable flight by the classifiers. The blue lines in each top subfigure indicate the thresholds of each discriminator. According to the figures, while data including rapid changes represented by rising and falling edges of roll angles are dropped from the stable flight, graduate changes such as decent phase decreasing altitude are accepted. These facts conclude the proposed classifier works as expected.

To utilize the stable data recognized by the proposed method, lift coefficient C_L is computed by using the data. For the computation, steady flight is always assumed. The data is segmented into 5 seconds data, i.e., 50 samples, and their mean values are utilized. Aircraft weight is estimated by subtracting fuel consumption calculated by accumulating fuel flow command of FADEC from initial takeoff weight.

The computed coefficients are shown in Fig. 12 with their approximate lines denoted by $C_{L\alpha}\alpha + C_{L0}$. The horizontal axis of the figure indicates angle of attack α estimated by subtracting path angle Γ from pitch angle θ. According to the figure, the lift coefficient is well estimated with the stable data, because well-known linear relation between the coefficient and angle of attack is clearly reflected. However, the computation with the data recognized as not stable also seems to succeed because of the same reason.

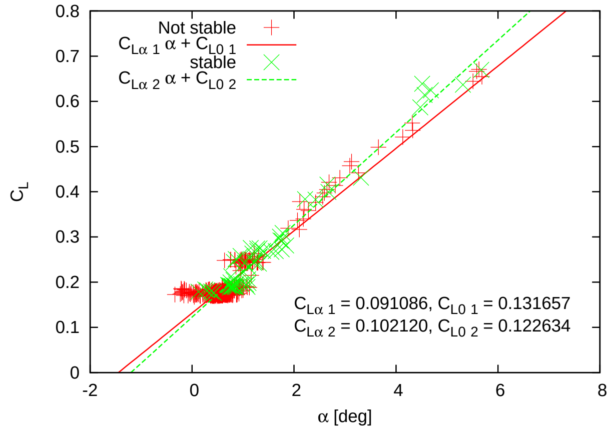

Fig. 12 Lift coefficient computed with data of “Flight 1”

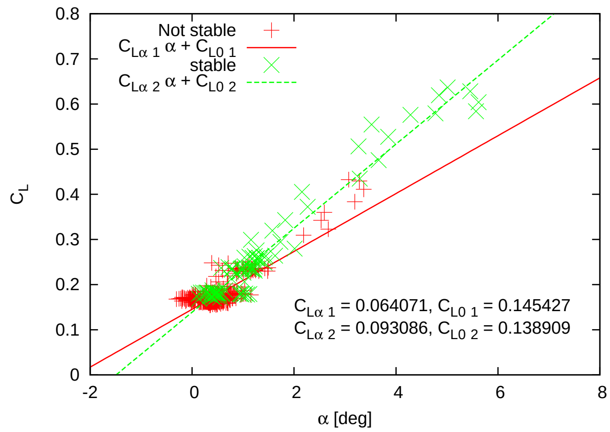

Fig. 13 Lift coefficient computed with data of “Flight 2”

For further analysis, additional three flights are analyzed and their lift coefficients are shown

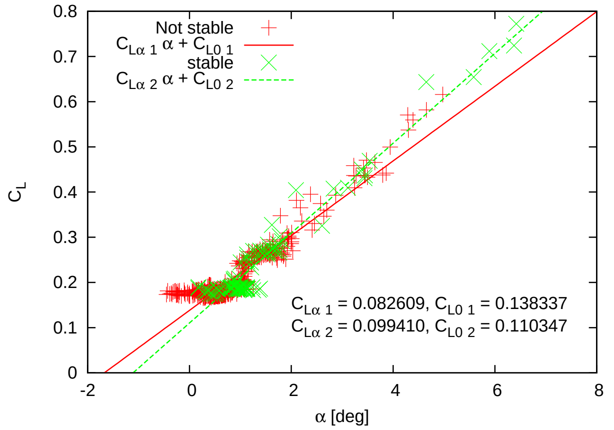

Fig. 14 Lift coefficient computed with data of "Flight 3"

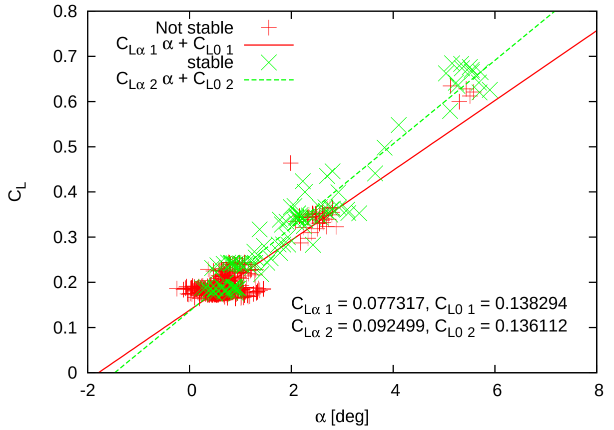

Fig. 15 Lift coefficient computed with data of "Flight 4"

Table 2 Properties of approximate lines of computed lift coefficients

Item	Stable		Not stable	
	$C_{L\alpha}$	C_{L0}	$C_{L\alpha}$	C_{L0}
Flight 1	0.102	0.123	0.091	0.131
Flight 2	0.093	0.139	0.064	0.145
Flight 3	0.099	0.110	0.083	0.138
Flight 4	0.092	0.136	0.077	0.138

in Fig. 13-15. Table 2 summarizes properties of the fitted lines of these four computations, and indicates that the $C_{L\alpha}$ results of the not stable data vary more widely than ones of the stable data. Therefore, we can conclude that the proposed classifier is sufficiently useful for extraction of the stable flight and estimation of flight performance.

5 Conclusion

This paper proposed the new classifier, which detected the stable flight by searching time-series flight data in order to utilize not only dedicated but also ordinal flight for performance estimation of aircraft. The classifier is characterized by utilization of the time-frequency information generated with the filter bank. In addition to the filter bank, the amplifiers and discriminator are comprised of the proposed method. The method has tunable parameters, which can be configured intuitively. The estimation results of lift coefficient by using the stable parts extracted from the real flight data with the proposed classifier was shown as the evaluations. The computed lift coefficient clearly indicated well-known linear relation to the angle of attack. Therefore, it concluded that the proposed classifier was effective.

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