Real-time unstable approach detection using sparse variational Gaussian process

Singh, Narendra Pratap; Goh, Sim Kuan; Alam, Sameer

2020

Singh, Narendra P., Goh, S. K., & Alam, S. (2020). Real-time unstable approach detection using sparse variational Gaussian process. Proceedings of the 2020 International Conference on Artificial Intelligence and Data Analytics in Air Transportation (AIDA-AT), 1-10. doi:10.1109/AIDA-AT48540.2020.9049174

<https://hdl.handle.net/10356/144652>

<https://doi.org/10.1109/AIDA-AT48540.2020.9049174>

© 2020 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works. The published version is available at:
<https://doi.org/10.1109/AIDA-AT48540.2020.9049174>

Downloaded on 26 Apr 2023 18:18:07 SGT

Real-time Unstable Approach Detection Using Sparse Variational Gaussian Process

Narendra Pratap Singh*, Sim Kuan Goh[†], Sameer Alam[‡]

Air Traffic Management Research Institute, School of Mechanical and Aerospace Engineering

Nanyang Technological University, Singapore

Email: {*np.singh | [†]skgoh | [‡]sameeralam }@ntu.edu.sg

Abstract—Worldwide, Air Navigation Service Providers (ANSP) are striving to exceed the desired safety levels. The Terminal Manoeuvre Area (TMA) is one of the most safety-critical areas in ATM as it encompasses the most critical phase of flight, i.e., departure and landing. An aircraft, during the final approach phase, is required to remain in a stable configuration and prevent any undesired state such as an unstable approach, which may subsequently lead to incidents/accidents such as Go-Around, Runway Excursions, etc. In this paper, we propose a data-driven framework to model the aircraft 4D trajectories in the final approach phase by adopting sparse variational Gaussian process (SVGP) model. The model is trained to learn the aircraft landing dynamics from Advanced Surface Movement Guidance and Control System (A-SMGCS) data, during the final approach phase. We experimentally demonstrate that SVGP provides an interpretable probabilistic bound of aircraft parameters that can quantify deviation and perform real-time anomaly detection. The findings of this work can increase situational awareness of the air traffic controller and has implications for the design of a new approach procedure in complex runway configurations such as parallel approach.

Index Terms—Unstable Approach, A-SMGCS, Instrument Landing System, Gaussian Process Model

I. INTRODUCTION

One of the key aspects of air transport is its high safety standards as compared to other modes of transport. However, growth in air traffic during the last decade and the projected growth worldwide has posed challenges to maintain it consistently. The most demanding phase of any flight is landing and take-off even though they amount less than 10% of the flying time of the aircraft. The safety data from the IATA GADM Accident database show that the approach and landing phases of flight account for the major proportion of all commercial aircraft accidents. 65% of the total accidents recorded from 2011 – 2015, unstable approaches were identified as a factor in 14% of those accidents [1]. The airline industry data shows that between 3% and 4% of approaches are unstable which means there are roughly 1,000 unstable approaches every day but pilots aborted the landing and executed go-around in only 3% of unstable approaches [2]. When an aircraft touches down the runway, it should have the correct configuration and speed to vacate the runway before it reaches the end. All aircraft (especially large body) in flight possess a great deal of energy (Kinetic as well as Potential energy). This energy must

eventually become zero when aircraft lands and stops. It is the responsibility of Pilots to manage this great deal of energy so that it leads to a successful and safe landing every time. However, the management of this energy and its appropriate dissipation are not always attained due to several factors like ATC procedures, ATC instructions, weather conditions, aircraft dynamics, etc.

An unstable approach not only leads to increased workload of the crew members (increased communication between the pilot and ATC), but it also significantly affects the workload of Air Traffic Control Officers (ATCOs), in the form of re-sequencing, merging and safety procedures when a go-around is initiated. An unstable approach may result in successful landing but it may lead to longer Runway Occupancy Time (ROT) or Runway excursion, which might result in accidents, degradation of runway capacity and flight delays. IATA runway excursion analysis report 2004-2009 shows that the most common single factor in landing excursions were unstable approaches and an associated failure to go-around [3].

As the data suggests, unstable approaches are carried out every day and the flight crews are in the best position to determine the safety of aircraft. Any significant variation in the aircraft parameters related to the stability of aircraft (described in Section II-A) can be observed by air-crew but it is very difficult for ATCOs to observe deviation in these parameters, especially in the busy traffic scenario. With the experience, certain ATCOs may identify the unstable approach and may point it out to the crew members. Once the crew members are alerted by ATCOs, they may reconsider their decision to land or go-around. Moreover, for simultaneous approaches on the parallel runway where safety requirement is very stringent, a slight deviation in trajectory may jeopardise the safety and can be fatal at times. The increase in air traffic will lead to a closely spaced parallel runway and simultaneous approaches on it. There will be a need for ground-based safety nets, which can trigger alerts and warnings to ATCOs for unstable approaches during the final approach and landing. Following this, the motivation of the current work is to develop a data-driven model to detect an unstable approach in real-time. Once this information is available to ATCOs, it will not only enhance overall safety but may also help them to reorganise traffic and develop arrival sequences accordingly.

This research has been partially supported under Air Traffic Management Research Institute (NTU-CAAS) Grant No. M4062429.052

There is limited literature on unstable approach detection

Fig. 1: Illustration of our proposed framework for landing profile analysis and real time detection of unstable approaches based on A-SMGCS data, ILS and runway configuration. It comprises ECEF transform, the approximation of ILS reference frame and Gaussian process modelling. The model provides landing profiles and can be used for anomaly detection.

and prediction [4], [5], [6]. Most of the work is the detection and analysis of major contributory factors for unstable approaches. The majority of the work carried out is from an air-crew perspective, i.e., detection of abnormality leading towards unstable approaches, if available, are presented to air-crew. The flight deck and surveillance data is analyzed by putting geometric boundaries along the ILS and outliers are detected to classify whether the approach was stable or unstable and a Nowcast algorithm is developed to predict unstable approaches using logistic regression method [4]. In [5], the authors try to detect unstable approaches utilizing flight data from Quick Access Recorder (QAR). They study to identify genuine unstable approaches by extracting Flight Management System data, which were never evaluated before. These data were reviewed by four flight data analysts making a group of two each. Kohens Kappa statistical measure was applied between the decisions of the two groups to classify genuine unstable approaches.

Yang, Huabo and Chun [6], analyzed the QAR data of 30,000 flights and found that around 10.3 % of the flights were unstable. Also, they identified IAS (Indicated airspeed)

and deviation on localizer were the most significant factors contributing towards the unstable approaches. The study was able to give some insight into factors affecting unstable approaches but it was confined to the B737 category of aircraft and again only QAR data was analyzed.

The available literature on unstable approaches are statistical analysis of QAR or surveillance data and most of the studies focus on the contributory factors of unstable approaches. The major gap in these studies are that they do not provide perspective from ATCOs and lack to provide real-time detection of unstable approaches. Nevertheless, they provide us sufficient information regarding the variables and parameters, which are most likely to contribute towards the stable and unstable phase of aircraft. The approach and methodology adopted in this work are from Air Traffic Management (ATM) perspective and a data-driven unsupervised machine learning approach is adopted for the detection of abnormal trajectories during the final approach.

Gaussian process (GP) provides a principal, practical and probabilistic approach to develop kernel machine for data modelling. GP has been used to address a variety of complex

problems ranging from numerical problems such as differential equations [7], uncertainty quantification [8] to real-world applications such as anomaly detection [9], [10], classification [11], regression [12], optimization [13], [14].

In aviation, the classical form of GP has been adopted in [15], [16] to visualize the 3D structure of historical aircraft trajectories in Dallas Fort Worth and Denver airport. GP suffers from high computational complexity in modelling a large amount of data. Several techniques have been developed to circumvent the complexity [17]. In this work, we adopted sparse variational GP [18] (SVGP) to model aircraft trajectories as well as their dynamics parameters for profile analysis and anomaly detection. SVGP significantly reduces the computational cost of GP and paves the way for real-time detection, compared to offline GP analysis done in [15], [16].

Based on our knowledge, existing methods (e.g., [4]) requires labelling of stability. Acquisition of the annotation can be time-consuming, subjective and error-prone. In our work, we attempt to avoid the annotation step by investigating unsupervised learning using SVGP. This approach models historical aircraft trajectories from a data-driven aspect, thereby reducing the need for the prior knowledge for feature extraction [4], [5]. Moreover, our methods provide continuous modeling of the landing phase compared to discrete modeling [4].

II. UNSTABLE APPROACH

There is no standard definition for the unstable approach but it can be defined as an approach during which an aircraft does not maintain at least one of the criteria, described by ICAO and FAA, as the stabilized parameter. Accordingly, airline's Standard Operating Procedures (SOP) stipulate that: at a predetermined height, 1000 feet to 500 feet for instruments or visual conditions respectively, an aircraft which is not within the parameters stated below, will lead to an unstable approach [19]

A. Stabilized Parameter:

- Aircraft on a correct path/track angle.
- Little changes in heading or bank are necessary to maintain approach trajectory.
- Speed no more than $V_{ref}+20$ Kts or no less than V_{ref} .
- Correct configuration for landing. Sink rate no more than 1000 ft per minute.
- Enough power for the landing configuration, no less than stipulated on the aircraft manual for approach.
- All landing instructions and checklist completed.
- In circle to land procedures level wings at 300 ft over airport elevation.

The airline's SOP clearly states that if any of the parameters are not met then the flight crew shall execute a missed approach or go around. However, due to fatigue, schedule or time pressure, lack of enough time to prepare the approach, ATC instructions, inappropriate management of altitude or speed, a last-minute runway change, early or late descents, lack of knowledge of parameters exceeding threshold values, wrong interpretation of time necessary to be stabilized, excessive

confidence between crew members and visual illusions leads an aircraft to an unstable approach phase.

Above-mentioned parameters are closely related to inappropriate management of aircraft energy and the energy equation of any aircraft of mass m can be written as:

$$\text{Total Energy} = \underbrace{\frac{1}{2}mv^2}_{\text{(Kinetic Energy)}} + \underbrace{mgh}_{\text{(Potential Energy)}}$$

where v is velocity and h is the altitude of aircraft. Though mass is also changing due to fuel consumption but in this paper, we assume it to be constant as the area of study is the final approach and landing, where the change is negligible. Thus velocity and altitude of an aircraft play an important role in an approach to be stable or unstable. Apart from this, on an Instrument landing system (ILS), deviation along localizer (LLZ) plays an important role in unstable approaches. In [20] in-depth analysis of these two deviations is carried out and it gives good insight to look at it from an unstable approach perspective. Also, ICAO documents [21], [22] provides the guidelines for instrument landing system and related design.

III. METHODOLOGY

In this paper, we develop a data-driven framework that models aircraft dynamics during the landing phase and monitors its adherence to the instrument approach chart, illustrated in Fig. 2. To achieve this, we build models to characterize historical aircraft dynamics and describe the probabilistic nature of the 4D trajectory measurements. The framework comprises procedures such as A-SMGCS data preparation, altitude error correction, earth-centered earth-fixed (ECEF) transformation, estimation of (ILS) reference frame and Gaussian process modeling.

A. A-SMGCS

Advanced Surface Movement Guidance Control System (A-SMGCS) is an amalgamation of multiple surveillance systems installed at airports to monitor the traffic movement in and around the airport. The A-SMGCS data used for analysis is provided by the Civil Aviation Authority of Singapore (CAAS). These tracks compile all arrivals and departures at Changi International Airport, Singapore. The recorded data comprehends the aircraft flight tracks in terms of single data points (position of aircraft in latitude and longitude, aircraft identity, reported altitude and velocity). The data is updated and recorded at a rate of 1 sec and complemented by flight plan data. This is one of the advantages of using A-SMGCS data over RADAR data where the minimum update rate is 4 seconds. Moreover, the data set comprises all categories (Heavy, Medium, and Light) of aircraft and also different types of aircraft in comparison to the QAR data (which is aircraft specific). In detail, the following useful information forms a data block:

- Timestamp, measured in seconds (From mid-night to mid-night)

Fig. 2: Our proposed methodology for training and inference of aircraft landing using SVGP.

- Horizontal positional information Latitude and Longitude in UTM WGS84 format
- Vertical positional information altitude in feet above mean sea level
- Ground speed in meter per second
- Aircraft wake-turbulence category

Since A-SMGCS is surveillance equipment meant for ATCOs decision making, altitude information is presented to the nearest 100 feet. Heading and landing runway information is not present in A-SMGCS data. Instead of heading, track/path angles of trajectories are derived after processing the A-SMGCS data and similarly landing runways are also assigned to each trajectory. The calculated horizontal position in the Cartesian coordinate is available in A-SMGCS data but the A-SMGCS reference origin coordinate is not known to us, therefore, we used the WGS84 format of latitude and longitude for horizontal position information.

In this work, two months (i.e., Oct and Nov 2017) of A-SMGCS data are utilized. The first month data is used for the training of SVGP while the second month is used for validation. A total of 2212 the medium category and 2305 of the heavy category are extracted for runway 02L for training, while 3162 from medium category and 2813 from the heavy category are extracted for validation.

B. Experiment

We focus on trajectory segments where aircraft is supposed to be aligned with ILS signals. We extract 4D trajectories segment $S(t_s, t_e)$ of interest where aircraft travel from time t_s to t_e second. The following are the extraction rules:

- $t_s = \max(t_1, t_2)$
- t_1 is the timestamp an aircraft descent to an altitude of 2500 feet
- t_2 is the timestamp an aircraft enter region R of interest (i.e., the rectangle defined by AKIPO (a fix at 7.8 NM from touchdown and on ILS, as published in IAP chart) and touchdown threshold at runway 02L).
- t_e is the timestamp an aircraft descent to an altitude of 100 feet.
- From time t_s to t_e second, an aircraft is aligning with the localizer (i.e., $< 3^\circ$ deviation) at least 50% of the time.

In A-SMGCS, the altitude information of the aircraft was rounded to the nearest 100 feet, h . Although the resolution is sufficient for ATCO to make decisions and planning, this

quantization procedure distorts the altitude measurement and can severely deteriorate modelling accuracy. Hence, altitude correction is required. As the landing procedure is well structured, we correct the altitude by a polynomial curve fitting (i.e., $h' = f(X, Y)$) of order 1, where X and Y are the Cartesian coordinates of aircraft's position.

Given latitude u , longitude i and altitude h' , ECEF Position of an aircraft p can be obtained using the following formulas:

$$\bar{p} = \begin{bmatrix} \bar{p}_x \\ \bar{p}_y \\ \bar{p}_z \end{bmatrix} = \begin{bmatrix} r_s \cos(\lambda_s) \cos(i) + h' \cos(u) \cos(i) \\ r_s \cos(\lambda_s) \sin(i) + h' \cos(u) \sin(i) \\ r_s \sin(\lambda_s) + h' \sin(u) \end{bmatrix} \quad (1)$$

$$\lambda_s = \text{atan}((1 - f)^2 \tan(u)) \quad (2)$$

$$r_s = \sqrt{\frac{R^2}{1 + (1/(1 - f)^2 - 1) \sin^2 \lambda_s}} \quad (3)$$

where R denotes the equatorial radius and f denotes flattening. This ECEF transform provides the 4D trajectories that are represented in the same unit, meter.

Next, the 4D trajectories are re-referenced using the ILS reference frame. ILS reference frame can be derived using vector algebra if the coordinates of the intermediate fixes are given. However, the altitude information presented in the ILS chart is rounded to the nearest 100 feet. We also observed that the intermediate fixes do not lie in the same line. Hence, we choose to estimate of ILS reference frame from data. The advantage of an estimated ILS reference frame is that the model can be tested on the approaches where there is no ILS facility available, like non-precision approaches or satellite-based approaches. Singular value decomposition is applied to derive the ILS frame by approximation through the basis that best explain the variation of 4D trajectory distributions. The new reference frame provides the vertical and lateral view during the landing phase, relative to the ILS frame. The data projected to the new reference frame is provided in Fig. 3 & Fig. 4.

C. Gaussian Process

Gaussian process (GP) is a Bayesian machine learning method that has advantages such as making a prediction, providing model uncertainty and being a generative model. These advantages can be utilized to characterize our data from several aspects. First, the predictive analysis facilitates

(a) Localizer

(b) Glide path

(c) Track Angle

(d) Speed

Fig. 3: Parameters' deviation for medium category. (a) deviation from localizer, (b) deviation from glide path, (c) deviation in track angle and (d) deviation in speed.

(a) Localizer

(b) Glide path

(c) Track Angle

(d) Speed

Fig. 4: Parameters' deviation for heavy category. (a) deviation from localizer, (b) deviation from glide path, (c) deviation in track angle and (d) deviation in speed.

the analysis of the relationship between input and output. Second, the model uncertainty quantifies the deviation of the parameters. Third, the probabilistic model can be used for anomaly trajectory detection. Fourth, the generative model learns the underlying data distribution, thus it can synthesize 4D trajectories that are similar to the historical data.

Given $D = (x_i, y_i)_{i=1}^N = (X, Y)$, Gaussian process model learn the probabilistic mapping function $f(x)$:

$$y_i = f(x_i) + \epsilon_i \quad (4)$$

where $f \sim GP(\cdot|0, k)$ and $\epsilon_i \sim N(\cdot, \sigma^2)$.

The predictive distribution for a new data point x_* can be obtained as follows:

$$p(y_*|x_*, X, y) = N(\mu_*, \sigma_*^2) \quad (5)$$

where $\mu_* = K_{*N}(K_N + \sigma^2 I)^{-1}y$ and $\sigma_*^2 = K_{**} - K_{*N}(K_N + \sigma^2 I)^{-1}K_{N*} + \sigma^2$. Hence, the GP provides prediction u_* and uncertainty σ_* given x_* .

The basic form of the aforementioned GP assumes the parameter σ in the likelihood to be a constant. In real-world applications, the likelihood can be input dependent, where $\epsilon_i \sim N(\cdot, \sigma_i^2)$. Based on the observation in Fig. 3 and 4, the variation of aircraft dynamics are observed to be changing along the landing phase. The phenomenon is also reported in studies [23]. In order to model the variation during the final approach phase, heteroscedastic likelihood [23] has to be incorporated into the GP model. The likelihood allows our GP model to characterize the uncertainty bounds (i.e., deviation in parameter) for different parts of the landing phase.

One issue of the basic form of GP is the computational complexity of $O(N^3)$. This complexity hinders the application of GP to big data. The GP community first addressed the issue via low-rank approximation of the kernel matrix. However, it is observed to be an ineffective method. Sparse variational GP (SVGP) [18] introduces a variational inducing point framework to reduce the complexity to $O(NM^2)$ and enable stochastic optimization. The complexity of inference is $O(M^2)$. The formulation of SVGP facilitates GP to model millions of data and show superior performance compared to state-of-the-art methods on benchmark data sets.

In our work, SVGP is adopted to model the aircraft's historical dynamic parameters. The "rbf" kernel is selected for SVGP with inducing points of 200. The number of training iteration is set to be 1000 epochs. SVGP model can be trained to perform the following analysis:

- The historical vertical profile w.r.t. ILS reference frame.
- The historical lateral profile w.r.t. ILS reference frame.
- The historical speed profile w.r.t. ILS reference frame.
- The historical track angle profile w.r.t. ILS reference frame.

Hence, aircraft profiles from different wake turbulence categories (WTC) can be compared and analysed. Moreover, the probabilistic modelling of the parameters (Horizontal and vertical deviation on ILS, aircraft speed and aircraft track

angle along the ILS reference frame) can also be used for the detection of anomaly trajectories. The anomaly score can be defined using the z -score (i.e., $z = (x - \mu)/\sigma$). The z -score is associated with probability in Gaussian distribution. Hence, at any timestamp, the probability is defined for each parameter of aircraft dynamics.

IV. RESULTS AND DISCUSSION

The section describes the results and experimental findings of our proposed methods on A-SMGCS data. It includes ILS re-reference, profile analysis, anomaly detection, analysis of the relationship between anomalous parameters and some case studies.

A. ILS Re-reference

Using the ILS reference frame learned from the training data, Fig. 3 and 4 show the re-referenced aircraft parameters from the validation month. Deviations in localizer, glide path, track angle and speed are observed.

From the re-referenced aircraft parameters, the heavy category aircraft are generally observed to have larger localizer deviations. There is nothing much to compare in glide path deviation in these two categories of aircraft. It is evident from Fig. 3 and 4 that the track angle contains some noise. The speed of the heavy category aircraft is higher than the medium category after passing FAF.

B. Landing Profiles

Fig. 5 shows the estimated probabilistic deviations of aircraft parameters along the landing phase. The figure is generated based on the probabilistic bound of SVGP, which provides confidence intervals of parameters' values. The bound is selected to be 2 and 3 standard deviations from the mean, which explain 95% and 99.7% of the data. Comparison between medium and heavy category are shown.

The track angle shows an abrupt burst near the touchdown of the runway because of noise in data. The probabilistic bounds for localizer and heading, in the beginning, are larger since aircraft are still being vectored in this area and yet to intercept the localizer. The deviation on the localizer for the medium category is higher than the heavy before the interception of localizer, which is common because of inertia.

The upper bound of glide path deviation is more for the Medium category than heavy. Once aircraft is established on the localizer, the deviations in all the parameters are constant except the speed. Speed of the aircraft decreasing gradually before it becomes constant. The decrease in speed is slightly higher before the Final Approach Fix (FAF). Thus the learned SVGP model is able to capture the approach path and flight profile of the aircraft very well.

C. Relationships between of Anomaly Parameters

To investigate the relationships between anomaly parameters, we analyze the number of co-occurrences between anomaly parameters. P_i^l and P_i^u denotes parameter i is falling

Fig. 5: SVGPs' estimated mean and standard deviation (i.e., 2σ and 3σ are provided) and shows bounds for (a) localizer, (b) glide path, (c) Track Angle, (d) speed respectively. The dotted line represents the mean, 2σ and 3σ for the medium category while the solid line represents the mean for the heavy category and its associated deviation is represented in solid green and light green colour respectively.

outside the lower(l) and upper(u) bounds of 3 standard deviation of the Gaussian distribution described by SVGPs, where i are (1) localizer, (2) glide path, (3) track angle, and (4) speed.

Table I to IV depicts this relationship between medium and heavy category aircraft before and after FAF. Each entry represents the percentage of co-occurrences between parameters. The diagonal entries give the percentage of anomalies detected only due to each of the four parameters in both lower and upper bound. The off-diagonal entries of the table depict the percentage of flights having anomalies in two of the parameters simultaneously. Hence, relationships between every pair of parameters can be drawn. For example, in Table IV the second row and last column gives the percentage of aircraft having higher velocity and left deviation on localizer (which is 22 aircraft out of 2813). As we can see from the table, the outlier percentage is higher after FAF, which suggests that the aircraft is likely to be in an unstable profile.

We can see that the observed anomalies are less before FAF in both WTC aircraft as the probabilistic bounds are larger before FAF. We also observe that anomalies in all parameters for heavy category aircraft is more than medium category.

There is an evident relationship between track angle and

localizer deviation. Since the change in any of the parameters will affect the other during the final approach and we observe this in the co-occurrence table as well.

Since the track angle parameter has abrupt behaviour due to noise, we believe this stand-alone should not be considered for contributing factors of an unstable approach. Even if we ignore the outliers percentage due to the track angle, the other three parameters give us a good indication of the unstable behaviour of aircraft. Moreover, if we relax the probabilistic bound from 99.73% to 95%, then these numbers will be higher. We leave it to the user to decide how much accuracy they need to detect anomalies in these parameters.

D. Case Study: 10 Trajectories with the Highest Anomaly Scores

Fig. 6 and 7 show aircraft landing profiles that have the highest outlier scores after the FAF and these aircraft went on to complete the landing. Five trajectories that have the highest outlier scores on each side of the Gaussian curves are selected for every parameter. For these ten trajectories, in general, we observe that heavy category aircraft have a higher

(a) Localizer

(b) Glide path

(c) Track Angle

(d) Speed

(a) Localizer

(b) Glidepath

(c) Track Angle

(d) Speed

Fig. 6: 10 trajectories with the highest anomaly score in each of the parameters for the medium category. Green envelope represents 3σ probabilistic bound in all the parameters.

Fig. 7: 10 trajectories with the highest anomaly score in each of the parameters for the heavy category. Green envelope represents 3σ probabilistic bound in all the parameters.

%	P ₁ ^l	P ₁ ^u	P ₂ ^l	P ₂ ^u	P ₃ ^l	P ₃ ^u	P ₄ ^l	P ₄ ^u
P ₁ ^l	0.633	0.285	0.949	0.000	0.633	0.538	0.000	0.095
P ₁ ^u	0.285	0.569	0.095	0.000	0.633	0.506	0.032	0.095
P ₂ ^l	0.949	0.095	0.411	0.000	0.253	0.221	0.000	0.158
P ₂ ^u	0.000	0.000	0.000	0.000	0.000	0.032	0.000	0.000
P ₃ ^l	0.633	0.633	0.253	0.000	0.664	0.443	0.032	0.063
P ₃ ^u	0.538	0.506	0.221	0.032	0.443	0.759	0.032	0.158
P ₄ ^l	0.000	0.032	0.000	0.000	0.032	0.032	0.032	0.000
P ₄ ^u	0.095	0.095	0.158	0.000	0.063	0.158	0.000	0.348

TABLE I: Co-occurrence of anomaly parameters for the medium category before FAF.

%	P ₁ ^l	P ₁ ^u	P ₂ ^l	P ₂ ^u	P ₃ ^l	P ₃ ^u	P ₄ ^l	P ₄ ^u
P ₁ ^l	2.878	1.423	0.095	0.000	2.751	5.756	0.221	0.316
P ₁ ^u	1.423	5.376	0.158	0.000	9.393	4.965	0.664	0.474
P ₂ ^l	0.095	0.158	0.285	0.000	0.348	0.127	0.000	0.127
P ₂ ^u	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P ₃ ^l	2.751	9.393	0.348	0.000	3.510	6.452	0.854	0.633
P ₃ ^u	5.756	4.965	0.127	0.000	6.452	5.250	0.633	0.411
P ₄ ^l	0.221	0.664	0.000	0.000	0.854	0.633	0.980	0.000
P ₄ ^u	0.316	0.474	0.127	0.000	0.633	0.411	0.000	0.791

TABLE II: Co-occurrence of anomaly parameters for the medium category after FAF.

overall anomaly score than the medium category of aircraft except the LLZ deviation.

In Fig. 6 (a) & Fig. 7 (a), the model can capture the trajectories with the highest outlier score and these trajectories have higher chances for being unstable approach as we see more deviation on LLZ suggesting aircraft crossing LLZ several times to align with it even after passing FAF. Fig. 6 (b) shows that there is no significant deviation on glide path in upper bound even for the highest outlying score but there are large deviations in the lower bound which suggests that aircraft is well below glide path, which suggests that approach is likely to be unstable and probably in low energy state. From Fig. 7 (b), we observe that one trajectory depicts significant deviation in upper bound, which suggests that aircraft tries to capture glideslope from above, which is not advisable and hence has potential to be in an unstable approach phase with high energy state. In both Fig. 6 (d) & Fig. 7 (d) the higher bound suggest that approach being made with higher as well as lower velocity than desired and hence is likely to be in an unstable approach phase with high and low energy state, respectively.

V. CONCLUSION AND FUTURE WORK

In this paper, Gaussian process model is utilized to learn historical aircraft dynamics and detect anomaly aircraft parameters in A-SMGCS data. As the model has continuous resolution, anomaly detection can be performed at any timestamp and location along the approach path. As we do not make any simplification or assumption of the problem, the model is ready for real-time anomaly detection. This work can be utilized as a safety net to generate alerts & warnings to ATCOs to enhance their situational awareness. Also, it provides a good opportunity to the ATCOs to alert the flight crews to

%	P ₁ ^l	P ₁ ^u	P ₂ ^l	P ₂ ^u	P ₃ ^l	P ₃ ^u	P ₄ ^l	P ₄ ^u
P ₁ ^l	0.696	0.759	0.316	0.063	0.696	0.886	0.000	0.095
P ₁ ^u	0.759	1.581	0.095	0.063	1.202	1.423	0.000	0.190
P ₂ ^l	0.316	0.095	0.253	0.000	0.127	0.063	0.000	0.127
P ₂ ^u	0.063	0.063	0.000	0.063	0.063	0.063	0.000	0.000
P ₃ ^l	0.696	1.202	0.127	0.063	0.696	0.633	0.000	0.000
P ₃ ^u	0.886	1.423	0.063	0.063	0.633	1.486	0.032	0.127
P ₄ ^l	0.000	0.000	0.000	0.000	0.000	0.032	0.000	0.000
P ₄ ^u	0.095	0.190	0.127	0.000	0.000	0.127	0.000	0.348

TABLE III: Co-occurrence of anomaly parameters for the heavy category before FAF.

%	P ₁ ^l	P ₁ ^u	P ₂ ^l	P ₂ ^u	P ₃ ^l	P ₃ ^u	P ₄ ^l	P ₄ ^u
P ₁ ^l	4.444	2.595	0.427	0.142	4.230	7.501	0.320	0.498
P ₁ ^u	2.595	7.892	0.355	0.071	11.838	7.288	1.066	0.782
P ₂ ^l	0.427	0.355	0.640	0.000	0.818	0.284	0.000	0.249
P ₂ ^u	0.142	0.071	0.000	0.142	0.107	0.107	0.000	0.036
P ₃ ^l	4.230	11.838	0.818	0.107	5.510	8.070	1.422	0.960
P ₃ ^u	7.501	7.288	0.284	0.107	8.070	7.679	1.102	0.675
P ₄ ^l	0.320	1.066	0.000	0.000	1.422	1.102	1.600	0.000
P ₄ ^u	0.498	0.782	0.249	0.036	0.960	0.675	0.000	1.280

TABLE IV: Co-occurrence of anomaly parameters for the heavy category after FAF.

correct the flight profile or to initiate a missed approach or go around, if there is persistent anomaly observed during the final approach. Moreover, for a closely spaced parallel approach, it will provide a good safety tool to ATCOs. This model can also be applied for anomaly detection leading to an unstable approach where approaches are being made without ILS, for example, non-precision approach or Performance-based navigation (PBN) approaches.

While this work focuses on anomaly detection and analysis in the landing phase, it has the potential to be extended from multiple aspects. First, the real-time detection model can be extended to have a look-ahead anomaly detection capability. This feature can facilitate better planning and organisation of air traffic by an ATCO. Second, this work focuses on univariate modelling of aircraft parameters, extension to multivariate models can provide an improved modelling accuracy. Third, the model can be used to analyse the impact of weather, wind, and monsoon to aircraft landing profiles. Fourth, it paves the way to develop parallel approaches to an airport by quantifying the landing space required.

REFERENCES

- [1] IATA, “Unstable approach : Risk mitigation policies, procedures and best practices 2nd edition.” [Online]. Available: <https://www.iata.org/whatwedo/safety/runway-safety/Documents/unstable-approaches-2016-2nd-edition.pdf>.
- [2] FlightGlobal.com, “safety-experts-call-attention-to-prevalence-of-unstable-approaches.” [Online]. Available: <https://www.flightglobal.com/news/articles>.
- [3] ICAO, “Stable approaches.” [Online]. Available: <https://www.icao.int/MID/Documents/2014>.
- [4] L. Sherry and J. Shortle, “Improving the nowcast of unstable approaches,” *8th International Conference on Research in Air Transportation*, 2016.

- [5] R. de Boer, "The automatic identification of unstable approaches from flight data." *6th International Conference on Research in Air Transportation*, 2014.
- [6] C. W. . J. H. Yang Jiao, Huabo Sun, "Research on unstable approach detection of civil aviation aircraft," *8th International Congress of Information and Communication Technology (ICICT)*, 2018.
- [7] C. Archambeau, D. Cornford, M. Opper, and J. Shawe-Taylor, "Gaussian process approximations of stochastic differential equations," *Journal of machine learning research*, vol. 1, pp. 1–16, 2007.
- [8] I. Bilonis, N. Zabarar, B. A. Konomi, and G. Lin, "Multi-output separable gaussian process: Towards an efficient, fully bayesian paradigm for uncertainty quantification," *Journal of Computational Physics*, vol. 241, pp. 212–239, 2013.
- [9] K.-W. Cheng, Y.-T. Chen, and W.-H. Fang, "Video anomaly detection and localization using hierarchical feature representation and gaussian process regression," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 2909–2917.
- [10] W. Herlands, E. McFowland III, A. G. Wilson, and D. B. Neill, "Gaussian process subset scanning for anomalous pattern detection in non-iid data," *arXiv preprint arXiv:1804.01466*, 2018.
- [11] D. Milios, R. Camoriano, P. Michiardi, L. Rosasco, and M. Filippone, "Dirichlet-based gaussian processes for large-scale calibrated classification," in *Advances in Neural Information Processing Systems*, 2018, pp. 6005–6015.
- [12] M. Raissi, H. Babaee, and G. E. Karniadakis, "Parametric gaussian process regression for big data," *Computational Mechanics*, vol. 64, no. 2, pp. 409–416, 2019.
- [13] M. Mlakar, D. Petelin, T. Tušar, and B. Filipič, "Gp-demo: Differential evolution for multiobjective optimization based on gaussian process models," *European Journal of Operational Research*, vol. 243, no. 2, pp. 347–361, 2015.
- [14] A. T. W. Min, Y.-S. Ong, A. Gupta, and C.-K. Goh, "Multiproblem surrogates: transfer evolutionary multiobjective optimization of computationally expensive problems," *IEEE Transactions on Evolutionary Computation*, vol. 23, no. 1, pp. 15–28, 2017.
- [15] W. J. Eerland, S. Box, and A. Söbester, "Modeling the dispersion of aircraft trajectories using gaussian processes," *Journal of Guidance, Control, and Dynamics*, pp. 2661–2672, 2016.
- [16] W. J. Eerland, S. Box, H. Fangohr, and A. Söbester, "A gaussian process based decision support tool for air traffic management," in *17th AIAA Aviation Technology, Integration, and Operations Conference*, 2017, p. 4264.
- [17] M. Bauer, M. van der Wilk, and C. E. Rasmussen, "Understanding probabilistic sparse gaussian process approximations," in *Advances in neural information processing systems*, 2016, pp. 1533–1541.
- [18] J. Hensman, A. Matthews, and Z. Ghahramani, "Scalable variational gaussian process classification," 2015.
- [19] IATA, "Runway safety documents." [Online]. Available: <https://www.iata.org/whatwedo/safety/runway-safety/Documents/unstable-approaches-2016-2nd-edition.pdf>.
- [20] T. H. . M. Soares, "Analysis of localizer and glide slope flight technical error," *27th Digital Avionics Systems Conference, IEEE/AIAA*, 2008.
- [21] ICAO, "Icao annex - 10. aeronautical telecommunications. volume 1, "radio navigation aids", 6th edition," *July*, 2006.
- [22] —, "Icao annex - 14. aerodromes. volume 1, "aerodromes design and operations, 5th edition," *July*, 2009.
- [23] K. Kersting, C. Plagemann, P. Pfaff, and W. Burgard, "Most likely heteroscedastic gaussian process regression," in *Proceedings of the 24th international conference on Machine learning*. ACM, 2007, pp. 393–400.