Development of a New Airport Unusual-Weather Detection System With Aircraft Surveillance Information

Shau-Shiun Jan, *Member, IEEE*, and Ya-Tzu Chen

***Abstract*— This paper proposes a new aviation unusual-weather detection system constructed to augment existing aviation unusual-weather alert systems. Due to a lack of ground meteorological stations with sufficient ground altitude near airports, existing aviation unusual-weather alert systems can only detect unusual-weather conditions near the ground surface. Thus, this paper uses the automatic dependent surveillance—broadcast (ADS-B) signal transmitted by commercial aircraft to acquire vertical weather information for low-level weather conditions. Specifically, we propose an aviation unusual-weather detection model to establish the system using both the aircraft irregular-movement detection algorithm and the machine learning method. The performance of the proposed unusual-weather detection model is validated with actual ADS-B signals from several flights collected at the airport. The experiment results show the accuracy rates of aviation normal/unusual-weather classification above 96% and false positive rates below 1% for decent flight phases.**

***Index Terms*— Automatic dependent surveillance - broadcast, aviation unusual weather, support vector machine.**

I. Introduction

WEATHER has been closely linked with flight safety. Many aviation accidents occur due to unusual-weather conditions even with advances in aviation technology [1], [2]. Unusual-weather reduces airline operating efficiency, forcing landing at other airports and cancellations of flights. In Taiwan, weather hazard impact is most intense during take-off and landing because of the region's topography. Airports need to acquire weather hazard information and alert aircraft within the region to pay attention to flight safety threats. However, existing aviation unusual-weather detection systems utilize ground-based meteorological observation stations to obtain this information in the Taipei Flight Information Region (FIR) [3], [4]. Since all ground-based meteorological observation stations are almost at the same altitude, they can only supply two-dimensional weather information near the ground [5]. As a result, accurate weather information about low-level weather conditions for climbing and landing aircraft is challenging to acquire.

To solve this problem, onboard sensor data from aircraft near airports is used to augment existing systems for obtaining vertical weather information. In this research, Automatic Dependent Surveillance – Broadcast (ADS-B) messages transmitted from aircraft are used for acquiring weather information. This system is a part of the Federal Aviation Administration's (FAA's) Next Generation Air Transportation System (NextGen) which is designed to improve the safety and efficiency of air traffic management. All U.S. and European aircraft are required to carry ADS-B transponders by 2020. Compared with traditional ground meteorological stations, we can directly receive the ADS-B signal from aircrafts to obtain weather information without building additional reference stations or systems. In other words, every aircraft can become an airborne meteorological observation station that will provide weather information for the purpose of detecting unusual-weather conditions. In this system, an aircraft determines its position information from a Global Navigation Satellite System (GNSS), and then uses an ADS-B transponder to broadcast its identifier and navigation information at specific time intervals. A ground station can receive the broadcasts and transmits the information to air traffic control for tracking the aircraft. Furthermore, the aircraft can receive ADS-B signals transmitted by other aircraft, and thus can be aware of other aircraft's positions [6], [7]. We develop a software defined radio receiver to collect and analyze all ADS-B messages, and by doing so, we can achieve the purpose of augmenting existing systems without installing any new ground meteorological stations at the airport.

ADS-B messages contain various data types according to the downlink format (DF) as shown in TABLE I. DF17 is commonly used to monitor aircraft motion, it contains position and velocity information of an aircraft. DF20 and DF21 can be further divided into three parts of short data link downlink messages (Comm-B messages) to derive aviation parameters [8], [9].

It is of significant practical interest to investigate the possibility of augmenting the current ground-based aviation weather alert system using aircraft ADS-B signal. Since the aviation parameters are used to find the correlation with unusual-weather information, preprocessing is necessary to ensure the quality of the received ADS-B data. The aviation parameters are obtained from airborne computers, and thus aircraft might contain systematic errors [10]. For this reason, an outlier detection process of the aviation parameters is essential during preprocessing. This paper applied the data screening ranges and outlier detection method to ensure the quality of ADS-B data. To find the correlations with the unusual-weather condition, the aircraft irregular movement

Manuscript received May 29, 2019; accepted June 28, 2019. Date of publication July 3, 2019; date of current version September 18, 2019. This work was supported by the Ministry of Science and Technology, Taiwan, under Grant 102-2221-E-006-079-MY3. The associate editor coordinating the review of this paper and approving it for publication was Dr. Sanket Goel.
(Corresponding author: Shau-Shiun Jan.)

The authors are with the Department of Aeronautics and Astronautics, National Cheng Kung University, Tainan 70101, Taiwan (e-mail: ssjan@mail.ncku.deu.tw; p48001182@mail.ncku.edu.tw).
Digital Object Identifier 10.1109/JSEN.2019.2926391

TABLE I
DOWNLINK FORMATS AND DATA CONTENT

	Message type	
DF 17	Aircraft identification	
	Airborne Position Message	
	Airborne Velocity Message	
	Comm-B Definition Subfield	**Message type**
DF 20 DF 21	4.0	Selected altitude
	5.0	Roll angle
		True airspeed
		True track angle
		Ground speed
	6.0	Magnetic heading
		Mach number
		Inertial vertical velocity

TABLE II
DATA SCREENING FOR ADS-B DATA

Message type	Data screening range
True airspeed (knots)	$50 \le v_a \le 850$
Ground speed (knots)	$50 \le v_g \le 850$
Mach number	$0 \le M \le 1$
Roll angle (°)	$0 \le \alpha_r \le 10$
Difference between true track angle and heading (°)	$\lvert \alpha_t - \alpha \rvert \le 45$

detection algorithm is used. As we show later in this paper, this proposed algorithm is verified by the official pilot reports. The official pilot reports are an effective validation source because they report actual weather conditions encountered by aircraft during flight. The pilot of an aircraft's records unusual-weather information and gives it to the ground facility after completing the flight mission.

Additionally, after these preprocesses of aviation parameters, these parameters are then used to build the aviation unusual-weather detection model via a machine learning method. Machine learning applies statistical techniques to automatically identify patterns in data to make accurate predictions [11], [12]. This paper applies the support vector machine (SVM) learning algorithm to build the unusual-weather detection model. SVM is commonly used for classification tasks that contain a high-dimensional classification of features in the learning model [13], [14]. It can thus be used to classify normal and unusual aviation weather conditions based on learning data.

Accordingly, the reminder of this paper is organized as follow. Section II discusses the aviation parameter preprocessing method. The aircraft irregular movement detection algorithm is discussed in Section III. In Section IV, the machine learning method to build an aviation unusual-weather detection model is explained. The verification results of the developed aviation unusual-weather detection model are given in Section V. Section VI presents a summary and concluding remarks.

II. AVIATION PARAMETER PREPROCESSING METHOD

An aircraft onboard sensors measure many aviation parameters for its flight safety management. These aviation parameters can be used to find the correlation with unusual-weather information. For this purpose, this paper first uses two aviation parameter preprocesses to check the quality of ADS-B data, namely data screening and outlier detection.

A. Data Screening Ranges for Aviation Parameters

ADS-B messages include various aviation parameters as depicted in TABLE I. To build an aviation unusual-weather detection model, this paper defines data screening ranges for aviation parameters. TABLE II presents the data screening ranges derived from ADS-B data. The commercial aircraft should fly at subsonic speed because of the aircraft's design, and the speed should be constrained within a certain range. Roll angle and the difference between true track angle and heading can also be constrained because they should be in a range in which commercial aircraft fly in normal conditions. This paper uses these constraints to check the quality of ADS-B data.

B. Outlier Detection Method for Aviation Parameters

ADS-B transponder is a kind of system in which electronic equipment onboard an aircraft automatically broadcasts its information via a digital data link. When it is working, some abnormal record or missing data occur due to noise or other possible electric disturbances. Therefore, the received ADS-B messages may contain some anomaly outliers or abnormal patterns, which will have significant impact on the analysis of ADS-B data. These outliers should be detected and excluded from the received ADS-B data. To deal with this problem, an effective median filtering method to detect outliers of received ADS-B data is applied. In this paper, the aviation parameters, which contain the position and velocity information of aircraft in ADS-B DF17 message type are used in this preprocess.

An outlier is defined as an anomalous data point or observation that deviates significantly with our expectations from the given dataset [15], [16]. In the received ADS-B data, these aviation parameters represent the flight of typical aircraft engine that is bound to laws of physics. According to ADS-B aviation parameters, outliers can be considered as data points which is contrary to the general pattern in the data sequence. These anomalous data would cause estimation biasing, false alarms or serious distortions on data analytical results because these observations do not follow the statistical distribution of the bulk of the data [17], [18].

There are various outlier detection techniques, criteria and researches that have already been used in a wide variety of applications [19]. Most outlier detection methods are usually based on assuming some well-behaving and independently distributed data. The statistical parameters, mean and variance, which are the two major factors in the presence of outlier detection method [20]. In these methods, the Hampel filter, which is based on well-know 3-sigma edit rule, regarded as one of the most robust and efficient outlier detection method [17]. This filter is replacing the estimates of original data location (mean) and scatter (standard deviation) in the 3-sigma edit rule, the median is substituted for the mean and the Median Absolute Deviation (MAD) is replaced for standard deviation. Because the median and MAD estimator both have much lower outlier sensitivities than the mean and standard deviation, the Hampel filter is usually much more effective than the 3-sigma edit rule [21]. There are only two tuning parameters of Hampel filter, namely the half-width K of the window and the threshold parameter T. For a dataset sequence x_k , the MAD scale estimate can be defined as:

$$S_k = 1.4826 \times \text{median}_{j\in[-K,K]} \left\{\left|x_{k-j} - m_k\right|\right\} \quad (1)$$

$$m_k = \text{median}\left\{x_{k-K}, \ldots x_k, \ldots x_{k+K}\right\} \quad (2)$$

The factor 1.4826 makes the MAD scale estimate an unbiased estimate of the standard deviation for Gaussian data [22]. The lower and upper bounds of Hampel filter based on the threshold parameter can be defined as follows:

$$\text{Bounds} = \begin{cases} m_k - T \times S_k \text{ (lower)} \\ m_k + T \times S_k \text{ (upper)} \end{cases} \quad (3)$$

In this paper, the Hampel filter is applied to detect outlier for aircraft position information data. To maintain the quality of ADS-B data, the data point is excluded from this dataset sequence if it is out of bound. The case studies are presented in the next section.

C. Case Studies of Outlier Detection

This paper chooses the tuning parameters $K = 3$ and $T = 3$ for these two case studies to show the response of Hampel filter [23]. These two cases were the aircrafts approaching Taiwan Taoyuan International Airport (ICAO airport code: RCTP) on 01/05/2016. First, the aircraft with ICAO number 89910A was selected to present the detection results, the position information was shown in Fig. 1. This aircraft was descending from 3,500 feet to 1,000 feet during the period, the outlier occurred in latitude information at the 147$^{\text{th}}$ seconds. The latitude changed from 25.0026° to 24.9891° (1.36 km) in 1 second. Another case was the aircraft with ICAO number 89910C, the outliers occurred in longitude and latitude information both at the 243$^{\text{th}}$ second period, as shown in Fig. 2. According to the aircraft trajectory shown in the lower right plot, this aircraft had 2.35 km displacement during a short period of time.

From these two case studies, the behavior of the Hampel filter is satisfactory in the preprocessing of ADS-B data. These

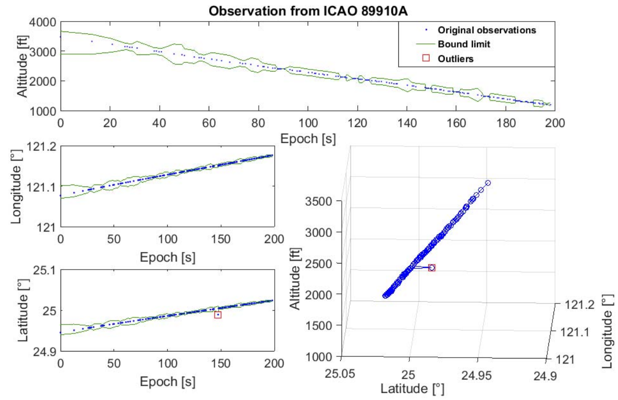

Fig. 1. Aircraft observations for the outlier detection case study I (Flight 89910A).

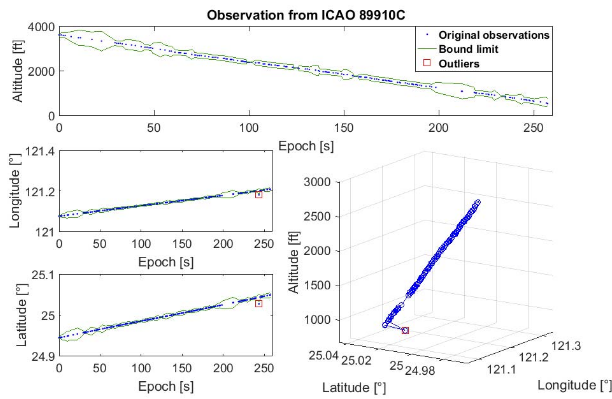

Fig. 2. Aircraft observations for the outlier detection case study II (Flight 89910C).

outliers can be detected and then excluded from ADS-B data sequence to ensure the data quality. After the aviation parameter preprocessing, these ADS-B data is used to verify the aircraft irregular movement detection algorithm. The aviation parameters are also used as features in the machine learning method to detect unusual-weather conditions.

III. Aircraft Irregular Movement Detection Algorithm

Instead of using the traditional aviation unusual-weather detection algorithm to retrieve aviation unusual-weather information, this paper uses another method to detect whether an aircraft is encountering aviation unusual-weather conditions. This method involves observation of the irregular movements of aircrafts during the approach and landing processes. The ADS-B system reports information about an aircraft's positon, altitude, and velocity values, for which the data are updated every 1 to 2 seconds. This information has a higher data update rate than the other weather parameters such as true airspeed and magnetic heading derived from ADS-B data. For this reason, the aircraft position information appears to be an effective source that can be used to detect aviation unusual-weather conditions due to its irregular movements. In this paper, approaching aircrafts are selected to execute

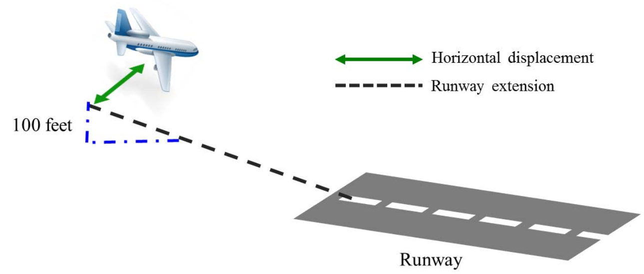

Fig. 3. Schematic illustration of the irregular movement detection algorithm for aircraft approaching the airport.

this detection method because they should descend along the required glide slope that extends from the airport runway, as illustrated in Fig. 3. The horizontal displacement can be determined as:

$$H\_disp = \text{distence}\left\{pos\_air\left(\phi_a, \lambda_a\right), ex\_line\left(\phi_l, \lambda_l\right)\right\} \quad (4)$$

where ϕ and λ denote latitude and longitude, respectively. In this detection method, the horizontal displacement is defined with the altitude of a given aircraft that is assessed at 100 feet intervals, and the standard deviation is calculated to identify the aircraft irregular movements. A larger horizontal displacement standard deviation value shows that there is a greater movement in the horizontal direction, and indicates that the aircraft might be about to encounter aviation unusual-weather conditions.

To verify the connection between the unusual-weather condition and this algorithm, the actual unusual aviation weather reports are used to prove this assumption. We collect pilot's report messages and conduct a cross validation with ADS-B data. TABLE III presents the validated information from actual flight cases with unusual-weather conditions. Irregular aircraft movements were detected for the flight level at which the pilot's report message was released. The flights marked with stars are chosen for unusual-weather conditions cases to show the validation results. In this algorithm, three actual flight cases were used to verify normal and unusual aviation weather conditions. The landing process for three aircrafts were chosen for the case studies, one for normal condition and others for aviation unusual-weather conditions.

The first case is the aircraft with ICAO number 78023E for normal weather conditions on 10/17/2015. Fig. 4 shows the recorded data information and derived parameters for this algorithm. The positive horizontal displacement value according to the airport runway data indicates that the aircraft is on the left side of the glide path approach direction, and vice versa. The standard deviation values are defined by the horizontal displacements as distinct from the previous 100 feet in altitude. In this normal weather case, the aircraft was approaching RCTP from 3,500 feet in 300 seconds, and the variations of its horizontal displacements were smooth, within a range -7 to 7 meters. The standard deviation values were stable, and were all below 3 meters during this landing process. According to this result, the aircraft was approaching the runway with a smooth landing and did not encounter any aviation unusual-weather conditions.

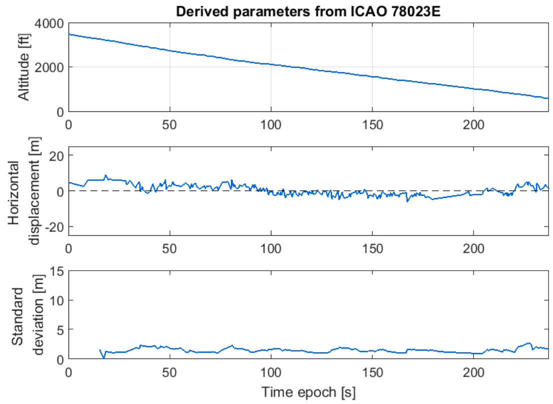

Fig. 4. Aircraft derived parameters for normal aviation weather condition (Flight 78023E).

TABLE III

VALIDATION OF UNUSUAL AVIATION WEATHER CONDITION CASES

Date	Pilot's report message	Irregular movement region (ft)
2015/10/17(*)	ARS CAL5155 N2505 E12114 FL009 OBS AT 0800Z MOD TURB=	1000 – 500
2015/10/19	ARS HDA264 N2505 E12114 FL005 OBS AT 0623Z MOD TURB=	900 – 500
2015/10/19(*)	ARS CAL0157 N2505 E12114 FL005 TO FL010 OBS AT 0730Z MOD TURB=	1100 – 500
2015/11/20	ARS EVA1200 N2505 E12114 FL002 TO FL020 OBS AT 0322Z LTG TURB=	2000 – 1500
2015/11/20	ARS CPA511 N2505 E12114 FL002 OBS AT 0332Z LTG TURB=	1000 – 500
2015/12/19	ARS CAL521 N2505 E12114 FL010 TO FL015 OBS AT 2045Z MOD TURB=	1500 – 1000
2016/01/07	ARS CAL018 N2505 E12114 FL002 TO FL008 OBS AT 0705Z MOD TURB=	1000 – 600

The second case is the aircraft with ICAO number 899102 for aviation unusual-weather conditions approaching RCTP. The pilot's report message was as follows: 'ARS CAL5155 N2505 E12114 FL009 OBS AT 0800Z MOD TURB=', which was released on 10/17/2015. Based on this report, flight CAL5155 encountered moderate turbulence at 900 feet at 8:00 UTC time. The derived flight information is presented in Fig. 5 when this flight was approaching RCTP from 3,500 feet in 250 seconds. Based on this result, aviation unusual-weather conditions can be observed from the 190th to the 240th second period as shown in the gray shaded area, and the recorded data shows that the aircraft was flown to the left side of the glide slope from the right side with more than 20 meters of horizontal displacement. The horizontal displacement thus changed dramatically in a short time due to a crosswind. The standard deviation values also jumped significantly from the 190th to the 240th second period, during which the values exceeded 10 meters in this case.

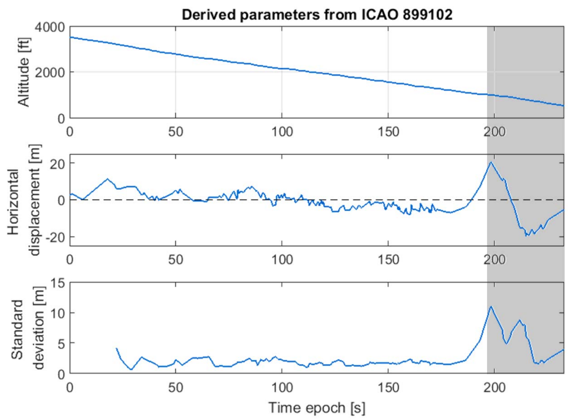

Fig. 5. Aircraft derived parameters for unusual aviation weather condition (Flight 899102).

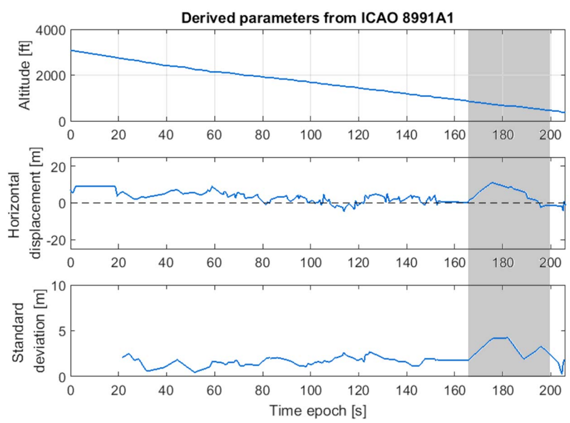

Fig. 6. Aircraft derived parameters for unusual aviation weather condition (Flight 8991A1).

The third case is the aircraft with ICAO number 8991A1 for aviation unusual-weather conditions on 10/19/2015. The pilot report released the following message: 'ARS CAL0157 N2505 E12114 FL005 TO FL010 OBS AT 0730Z MOD TURB=' to indicate that flight CAL0757 encountered a weather situation near RCTP. The message means that there was moderate turbulence at 1,000 feet at 7:30 UTC time. Based on the altitude information of this aircraft shown in Fig. 6, it was descending from 3,000 feet to 500 feet during this period. The reported turbulence information occurred at 1,000 feet from the 160th to the 200th seconds, as shown in the gray shaded area. This aircraft was flown to the right side of the glide slope, with more than 10 meters of horizontal displacement. The standard deviation values also jumped from the 165th to the 180th second period. These three cases indicate that the aircraft irregular movement detection algorithm can be used to observe aviation unusual-weather conditions when an aircraft is approaching an airport.

IV. Machine Learning Method

In order to utilize all the aircraft surveillance information, this paper also applies a machine learning method to build an aviation unusual-weather detection model in descent flight phases. TABLE VI provides a comparison of various

TABLE IV
COMPARISION OF VARIOUS MACHINE LEARNING METHOD

Performance measure	Navie Bayes	Decision Tree	K-Nearest Neighbor	SVM
Accuracy	84.82%	95.52%	93.47%	95.74%
Sensitivity	88.81%	85.01%	77.06%	76.81%
Specificity	84.32%	96.83%	95.52%	98.11%
Precision	41.47%	77.05%	68.25%	83.54%
False positive rate	15.68%	3.17%	4.48%	1.89%
Correlation	0.54	0.78	0.68	0.78

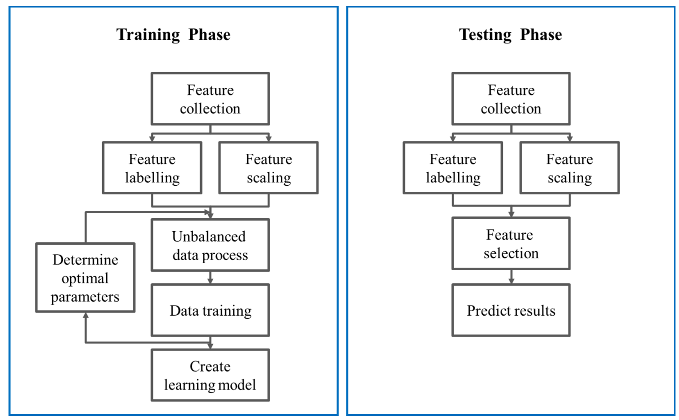

Fig. 7. The flow chart of the machine learning method.

machine learning methods with performance measures. Based on life safety considerations, this model is expected to provide good accuracy and fewer false positives related to classifying normal or unusual-weather conditions. The SVM learning algorithm was chosen to establish a database with normal and unusual-weather conditions because it provides better performance in this application. The details of these performance measures are discussed in the following section.

This section introduces the machine learning method and then gives analysis results of unusual-weather detection. The details of the machine learning method are discussed below. A flow chart is given in Fig. 7.

A. Feature preprocessing for machine learning method

The preprocessing of features includes feature collection, feature labelling and feature scaling. For detecting unusual-weather conditions using the machine learning method, a feature set is used to build the SVM learning model. TABLE V shows the nine features collected from ADS-B data. These features are directly derived from ADS-B DF 17, 20, and 21. The variation values of these message types are chosen as features because of their relationships with aviation weather conditions. For SVM learning algorithm, this paper determines the variation values with time at two epochs, which are 1 nautical mile apart, of a specific aircraft.

In the feature labelling process, the feature sets are defined as normal weather conditions or unusual-weather conditions

TABLE V
FEATURE SETS IN SVM ALGORITHM

Feature number	Feature name
#1	Vertical speed variation
#2	True airspeed variation
#3	Ground speed variation
#4	Mach number variation
#5	Magnetic heading variation
#6	Roll angle variation
#7	True track angle variation
#8	Track angle rate variation
#9	Inertial vertical velocity

TABLE VI
BOUNDS FOR SVM FEATURES FOR DESCENT PHASES OF FLIGHT

SVM features (unit)	Descent	
	min	max
Vertical speed (m/min)	0	24
True airspeed (knots)	0	1.6
Ground speed (knots)	0	1.6
Mach number	0	0.004
Magnetic heading (°)	0	0.9
Roll angle (°)	0	0.6
True track angle (°)	0	0.9
Track angle rate (°/s)	0	0.15
Inertial vertical rate (m/s)	0	20

according to the aircraft irregular movement detection algorithm and possible aviation unusual-weather conditions [24]. To make sure that the machine learning functions work properly with these features, the feature scaling procedure is used to standardize the range of independent features. These features are rescaled to range from 0 to 1, and the maximum and minimum values of each feature are defined from ADS-B data. This paper collected ADS-B data for 10 days, from 11/15/2015 to 11/24/2015, to acquire these maximum and minimum values. TABLE VI shows the bounds of these features with descent phases of flight. The scaled features can be determined using the following equation [25]:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{5}$$

where x' is the scaled value of a feature, and x is the original value of a feature. These scaled features are applied in the data training process. Then, the SVM learning model is built for detecting unusual-weather conditions.

B. Feature Selection Process

In order to improve the classification and prediction performance of the SVM learning model, a feature selection technique is used to filter corresponding features and remove relatively insignificant features [26]. Support vector machine recursive feature elimination (SVM-RFE) can be used for this purpose [27]. In SVM-RFE, as shown in Fig. 8, the ranking criterion for a feature can be defined from the following step. For high-dimensional feature spaces, the decision function in SVM is as follows:

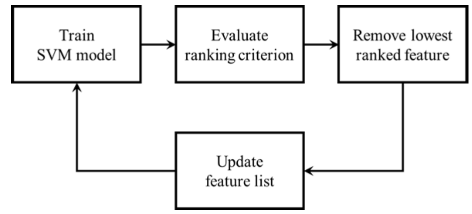

Fig. 8. SVM-RFE process of SVM learning model.

$$f(x) = w \cdot \varphi(x) + b \tag{6}$$

where w denotes the weight vector, $\varphi(x)$ is the conversion function for the input dataset, and b denotes a bias. The purpose of SVM is to maximize the margin of the hyperplane and then improve the distinguishing function between two classes of data. For the objective to optimize the distinguishing function, the primal problem can be regarded as:

$$\begin{aligned} &\min \frac{1}{2}\|w\|^2 \\ &\text{subject to } y_i(w \cdot \varphi(x) + b) \geq 1, i = 1, \ldots, l. \end{aligned} \tag{7}$$

To solve this problem, the Lagrangian formulation is used in this method, which can be written as:

$$L_D = \sum\nolimits_{i=1}^{n} \alpha_i - \frac{1}{2}\sum\nolimits_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j \varphi(x_i) \cdot \varphi(x_j) \tag{8}$$

where α denotes Lagrange multipliers and y denotes the class label. Because it is not easy to define the explicit form of $\varphi(x)$ in real world problems, the next step is to use kernel function $K(x_i, x_j)$ to replace $\varphi(x)$. The common choice for kernel functions is Gaussian kernel, it can be expressed as [28]:

$$K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2} \tag{9}$$

Then, the ranking criterion of a feature can be determined as:

$$\begin{aligned} R(k) = \frac{1}{2}\Big(\sum\nolimits_{i,j=1}^{n} &\alpha_i \alpha_j y_i y_j K(x_i, x_j) \\ &- \alpha_i \alpha_j y_i y_j K\left(x_i^{(-k)}, x_j^{(-k)}\right)\Big) \end{aligned} \tag{10}$$

where $(-k)$ means that feature k has been eliminated.

In SVM-RFE, each iteration includes four stages. A SVM learning model is trained in the first stage to evaluate the ranking criterion for each feature. The feature with the lowest ranking criterion is eliminated since it has the least contribution to the classification in the SVM learning model. This process is repeated until the performance is brought down to selected thresholds.

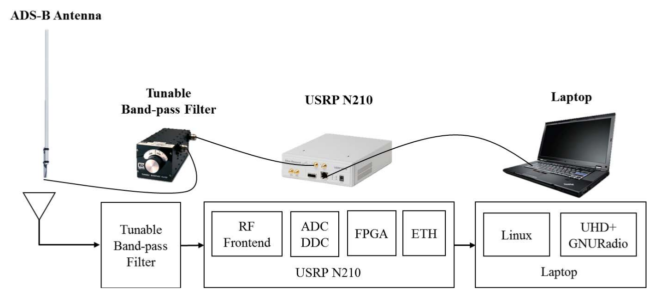

Fig. 9. The hardware architecture of the ADS-B software defined radio receiver.

TABLE VII
DATA SPECIFICATION IN NUMBER OF DATA SAMPLES

Total samples	Normal conditions	Unusual conditions	Unusual ratio
42435	39193	3242	7.64 %

V. EXPERIMENT SETUP AND PERFORMANCE RESULTS

A. Experiment Setup

This paper collected real aircraft surveillance information at the RCTP. The hardware architecture of the developed ADS-B software defined radio receiver is shown in Fig. 9. The ADS-B signal is received from the ADS-B antenna with a tunable band-pass filter. Through the RF front-end, the signals then pass to the Analog to Digital Converter (ADC) and Digital Down Converter (DDC) to be digitalized as baseband signals. The digital signals are processed in Field Programmable Gate Array (FPGA) and then the USRP Hardware Driver (UHD) and GNU Radio Companion (GRC) are used to communicate with the USRP N210 via the Gigabit Ethernet interface.

B. Performance Analysis Results

For demonstrating the SVM learning model and evaluating the performance of classification results, 3-day ADS-B data from 11/20/2015 to 11/24/2015 were collected for the data training process. Then, the testing ADS-B data collected on 11/28/2015 was used to verify the model. TABLE VII presents the training data specification in normal and unusual-weather conditions for descent flight phases. Based on the aircraft irregular movement detection algorithm and the actual released pilot report on 11/28/2015 (see Table VIII), the testing ADS-B data can be defined as normal or unusual-weather conditions. This means that the actual weather conditions are used for the testing ADS-B data. For this reason, we use the testing data to run a verification process and then provide the classification results. TABLE IX shows the contingency table of the success and failure in this testing process. In this paper, the classifier outcomes are stated as normal/unusual replacing negative/positive to avoid confusion. Furthermore, to evaluate the classification results of the SVM learning model, six performance measures were applied (see TABLE X) [29], [30].

Accuracy is the probability of differentiating normal and unusual-weather conditions correctly in all prediction results. Sensitivity is the ability to correctly identify unusual-weather conditions. Specificity is the rate which normal cases are identified correctly. Precision is the fraction of normal weather conditions classified correctly. The false positive rate is the proportion of unusual-weather conditions reported that are actually normal weather conditions. The correlation coefficient is defined as a measure between the real data and predicted classifications (ranges: 1 to -1). A correlation coefficient closer to 1 indicates better predictions.

TABLE VIII
RELEASED PILOT REPORT ON 11/28/2015

Date	Pilot's report message
2015/11/28	ARS EVA36 N2505 E12114 FL030 TO FL050 OBS AT 1222Z MOD TURB= ARS CDG4078 N2505 E12114 FL030 OBS AT 1227Z MOD TURB= ARS CPA531 N2505 E12114 FL030 OBS AT 1238Z MOD TURB=

TABLE IX
CLASSIFIER AND REALITY SPECIFICATIONS

Case	Classifier outcome	Reality (Truth)
True Positive (TP)	Unusual	Unusual
True Negative (TN)	Normal	Normal
False Positive (FP)	Unusual	Normal
False Negative (FN)	Normal	Unusual

TABLE X
PERFORMANCE MEASURES FOR SVM CLASSIFICATION RESULTS

Performance measure	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}\times 100\%$
Sensitivity	$\frac{TP}{TP+FN}\times 100\%$
Specificity	$\frac{TN}{TN+FP}\times 100\%$
Precision	$\frac{TP}{TP+FP}\times 100\%$
False positive rate	$\frac{FP}{TN+FP}\times 100\%$
Correlation	$\frac{TP\times TN-FP\times FN}{\sqrt{(TP+FN)\times(TP+FP)\times(TN+FP)\times(TN+FN)}}$

TABLE XI
CONTRIBUTION GRADE OF SVM FEATURES FOR DESCENT PHASES OF FLIGHT

Feature number	#1	#2	#3	#4	#5	#6	#7	#8	#9
	2	9	8	4	5	7	3	6	1

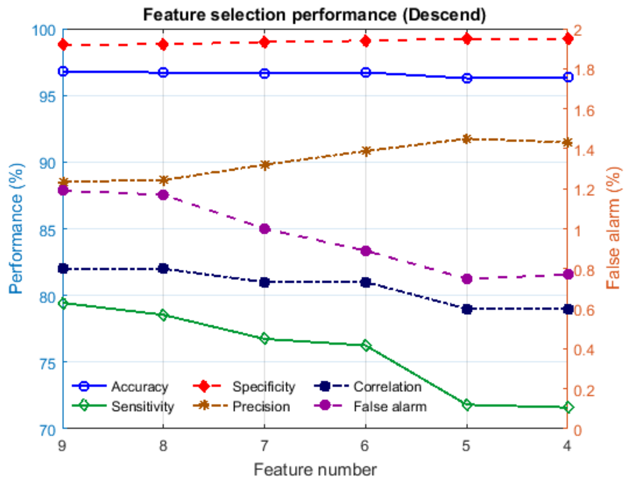

Fig. 10. Feature selection performance of original data.

TABLE XII
PERFORMANCE THRESHOLD FOR DESCENT PHASES OF FLIGHT

Performance	Sensitivity	Precision	Correlation
Threshold	75 %	85 %	0.75

To analyze the classification results, this paper applies a feature selection technique to obtain good performance in terms of predictions and classification with the least number of features. In this process, the contribution grades of each feature depend on the ranking criterion mentioned above (see TABLE XI). TABLE XI uses values of 1 to 9 to indicate the contribution grade; a higher value means that the corresponding feature is more important for building the SVM training model. For example, the true airspeed (i.e., feature number #2) and the ground speed (i.e., feature number #3) have the greatest contributions to distinguishing normal and unusual-weather conditions in this model. The features with lower contribution grades are removed from the original nine features in the recursive feature selection process. Moreover, the performance should be maintained on an acceptable quality with the original prediction results. The selected performance thresholds for descent flight phase are shown in TABLE XII. Fig. 10 shows the performance results of the feature selection process for the descent flight phases. Based on the result, accuracy and specificity do not significantly vary in this process, but sensitivity and the correlation coefficient drop when a few features are removed. The sensitivity rate drops 5% after the third feature is extracted. To meet the performance thresholds in TABLE XII, this paper chosen these features to build the SVM learning model with the descent flight phases (see TABLE XIII).

The classification results for descent flight phases after the feature selection process are presented in TABLE XIV. The six measures were used to evaluate performance. Even though the number of features was reduced by the feature selection process, the accuracy rates is close to 97%, and the false positive rates are below 1%. This indicates that

TABLE XIII
FEATURES FOR BUILDING SVM LEARNING MODEL FOR DESCENT PHASES OF FLIGHT

	Descent
Features	True airspeed Groundspeed Mach number Heading Roll angle Track angle rate

TABLE XIV
CLASSIFICATION RESULTS OF DATA FOR DESCENT PHASE

Classification results for descent phase Number of data points: 13792		**Reality (Truth)** Unusual	Normal
Classifier outcome	Unusual	1098	111
	Normal	342	12241
Accuracy		96.72%	
Sensitivity		76.25%	
Specificity		99.1%	
Precision		90.82%	
False alarm		0.89%	
Correlation		0.81	

the aviation unusual weather detection model is effective in detecting unusual weather conditions.

VI. CONCLUSIONS

To develop a new aviation unusual-weather detection system to enhance existing ground-based aviation unusual-weather alert systems, this paper proposed the use of the ADS-B signal and implemented an outlier detection process for aviation parameters and then established a model by applying a machine learning method. The Hampel filter was satisfactory in the preprocessing method with ADS-B position data for detecting the outlier. To find the correlation between the aviation parameters and aviation unusual-weather conditions, this paper proposed the aircraft irregular movement detection algorithm to achieve the goal. Three case studies were used to verify this algorithm with aircraft pilot reports. The aviation parameters were applied in the machine learning method as feature sets to build a learning model for aviation unusual-weather detection. Nine aviation parameters, which can be directly decoded from ADS-B data, were to construct an aviation unusual-weather detection model for descent flight phases. Furthermore, feature selection was used to enhance the classification results. The results of the learning model showed accuracy rates close to 97% and false positive rates below 1%. According to the results, aviation unusual-weather conditions can be successfully detected using the proposed aviation unusual-weather detection model with ADS-B signals.

REFERENCES

[1] A. J. Fultz and W. S. Ashley, "Fatal weather-related general aviation accidents in the United States," *Phys. Geography*, vol. 37, no. 5, pp. 291–312, 2016.
[2] *Statistical Summary of Commercial Jet Airplane Accidents*, Boeing, Chicago, IL, USA, Jul. 2017.
[3] H. P. Yu, "Introduction to LLWAS of RCTP&RCSS in Taiwan," Civil Aeronaut. Admin., Taipei, Taiwan, Tech. Rep., 2011.
[4] J. C. Chen and H. F. Yuan, "Improving low level wind shear alert system (LLWAS)," *J. Aviation Saf. Manage.*, vol. 1, no. 2, pp. 85–102, 2014.
[5] W.-K. Chen, *Linear Networks and Systems*. Belmont, CA, USA: Wadsworth, 1993, pp. 123–135.
[6] J. Scardina, *Overview of the FAA ADS-B Link Decision*. Washington, DC, USA: Federal Aviation Administration, 2002.
[7] W. R. Richards, K. O'Brien, and D. C. Miller, "New air traffic surveillance technology," Boeing, Chicago, IL, USA, Tech. Rep. QTR_02.10, 2010.
[8] *Minimum Operational Performance Standards for 1090 MHz Extended Squitter Automatic Dependent Surveillance—Broadcast (ADS-B) and Traffic Information Services—Broadcast (TIS-B)*, RTCA, Washington, DC, USA, 2009.
[9] J. Z. Sun. *The 1090 mhz Riddle—An Open-Access Book About Decoding Mode-S and ADS-B Data*. Accessed: May 28, 2019. [Online]. Available: http://mode-s.org/decode/
[10] S. de Haan, "High-resolution wind and temperature observations from aircraft tracked by Mode-S air traffic control radar," *J. Geophys. Res., Atmos.*, vol. 116, no. D10111, pp. 1–13, 2011.
[11] Y. S. Abu-Mostafa, M. Magdon-Ismail, and H. T. Lin, *Learning from Data*. New York, NY, USA: AML Book, 2012.
[12] J. Brownlee. *A Tour of Machine Learning Algorithms*. Accessed: May 28, 2019. [Online]. Available: http://machinelearningmastery.com/a-tour-of-machine-learning-algorithms/
[13] C. C. Chang and C. J. Lin, "LIBSVM: A library for support vector machines," *ACM Trans. Intell. Syst. Technol.*, vol. 2, no. 3, pp. 1–27, 2011.
[14] C. W. Hsu, C.-C. Chang, and C.-J. Lin, "A practical guide to support vector classification," Nat. Taiwan Univ., Taipei, Taiwan, Tech. Rep., 2016.
[15] R. K. Pearson, "Outliers in process modeling and identification," *IEEE Trans. Control Syst. Technol.*, vol. 10, no. 1, pp. 55–63, Jan. 2002.
[16] V. J. Hodge and J. Austin, "A survey of outlier detection methodologies," *Artif. Intell. Rev.*, vol. 22, no. 2, pp. 85–126, 2004.
[17] H. Liu, S. Shah, and W. Jiang, "On-line outlier detection and data cleaning," *Comput. Chem. Eng.*, vol. 28, pp. 1635–1647, Aug. 2004.
[18] R. K. Pearson, *Mining Imperfect Data: Dealing with Contamination and Incomplete Records*. Philadelphia, PA, USA: SIAM, 2005.
[19] P. Rana, D. Pahuja, and R. Gautam, "A critical review on outlier detection techniques," *Int. J. Sci. Res.*, vol. 3, no. 12, pp. 2394–2403, 2014.
[20] P. J. Rousseeuw, A. M. Leroy, *Robust Regression and Outlier Detection*. Hoboken, NJ, USA: Wiley, 1987, p. 329.
[21] R. K. Pearson, *Exploring Data in Engineering, the Sciences, and Medicine*. London, U.K.: Oxford Univ. Press, 2011, p. 792.
[22] R. K. Pearson, Y. Neuvo, J. Astola, and M. Gabbouj, "Generalized hampel filters," *EURASIP J. Adv. Signal Process.*, vol. 2016, p. 87, Jul. 2016.
[23] B. Júnior, A. Bezerra, and P. S. da Motta Pires, "An approach to outlier detection and smoothing applied to a trajectography radar data," *J. Aerosp. Technol. Manage.*, vol. 6, no. 3, pp. 237–248, 2014.
[24] *Flight Operations Briefing Notes—Adverse Weather Operations—Windshear Awareness*, Airbus, Leiden, The Netherlands, 2007.
[25] P. Juszczak, D. Tax, and R. P. Duin, "Feature scaling in support vector data description," in *Proc. 8th Annu. Conf. Adv. School Comput. Imag. (ASCI)*, 2002, pp. 95–102.
[26] A. Rakotomamonjy, "Variable selection using SVM based criteria," *J. Mach. Learn. Res.*, vol. 3, pp. 1357–1370, Mar. 2003.
[27] I. Guyon, J. Weston, S. Barnhill, and V. Vapnik, "Gene selection for cancer classification using support vector machines," *Mach. Learn.*, vol. 46, nos. 1–3, pp. 389–422, 2002.
[28] K. Yan and D. Zhang, "Feature selection and analysis on correlated gas sensor data with recursive feature elimination," *Sens. Actuators B, Chem.*, vol. 212, pp. 353–363, Jun. 2015.
[29] R. Kohavi and F. Provost, "Glossary of terms," *Mach. Learn.*, vol. 30, pp. 271–274, Jun. 1998.
[30] Y. Wang, J. Wong, and A. Miner, "Anomaly intrusion detection using one class SVM," in *Proc. IEEE 5th Annu. SMC Inf. Assurance Workshop*, Jun. 2004, pp. 358–364.

Shau-Shiun Jan received the Ph.D. degree in aeronautics and astronautics from Stanford University in 2003.

He is currently a Professor with the Department of Aeronautics and Astronautics, National Cheng Kung University (NCKU), Taiwan. He directs the NCKU Communication and Navigation Systems Laboratory. His research focuses on GNSS augmentation system design, analysis, and application.

Ya-Tzu Chen received the B.S. degree in aeronautics and astronautics from National Cheng Kung University (NCKU), Taiwan, in 2009, where she is currently pursuing the Ph.D. degree with the Department of Aeronautics and Astronautics.

Her research currently focuses on the application and analysis of the ADS-B signal.