Airplane Flight Phase Identification Using Maximum Posterior Probability Method

Nataliia Kuzmenko
Air Navigation Systems Department
National Aviation University
Kyiv, Ukraine
nataliiakuzmenko@ukr.net

Ivan Ostroumov
Air Navigation Systems Department
National Aviation University
Kyiv, Ukraine
ostroumovv@ukr.net

Yurii Bezkorovainyi
Aerospace Control Systems Department
National Aviation University
Kyiv, Ukraine
yurii.bezkor@gmail.com

Yuliya Averyanova
Air Navigation Systems Department
National Aviation University
Kyiv, Ukraine
ayua@nau.edu.ua

Vitalii Larin
Air Navigation Systems Department
National Aviation University
Kyiv, Ukraine
vjlarin@gmail.com

Olha Sushchenko
Aerospace Control Systems Department
National Aviation University
Kyiv, Ukraine
sushoa@ukr.net

Maksym Zaliskyi
Telecommunication and Radioelectronic Systems Department
National Aviation University
Kyiv, Ukraine
maximus2812@ukr.net

Oleksandr Solomentsev
Telecommunication and Radioelectronic Systems Department
National Aviation University
Kyiv, Ukraine
avsolomentsev@ukr.net

***Abstract*— The flight of a civil airplane is supported by many different systems. However, during the flight pilots require different navigation and surveillance data to perform airplane guidance. Each flight phase requires the usage of different methods of guidance and maintaining a preplanned trajectory. Automatic flight phase identification is an important component of on-board data processing and in the ground surveillance data processing unit. In the paper we study plight phase identification using a probability-based approach. Flight phase is detected by vertical speed and current barometrical altitude by method of the maximum posterior probability. A normal probability density function is used as a conditional function due to the assumption of normal error distribution of barometrical sensor. The proposed approach has been verified with real traffic surveillance data obtained under automatic dependent surveillance-broadcast communication channel within Ukrainian airspace. Classification on four common flight phases of taxing, take-off, en-route, and landing is used. The proposed method guarantees flight phase recognition with a minimum risk of false detection and indicates well detection in case of gaps in data sets.**

Keywords*— *data processing, surveillance data, airplane track, maximum posterior probability, barometrical altitude, ADS-B

I. INTRODUCTION

Aviation is one of the most developed transportation types. The number of air transportations is increased each year [1]. However, the capacity of airports and airspace are limited. Thus, further development of aviation requires improving the performance of an existing system, wide integration of robust control, and introducing a new air traffic concept. Each airplane flight is supported by Communication, Navigation and Surveillance services to guaranty the required level of safety.

Surveillance is an important component of the air transportation system. Surveillance equipment measures the location of each airspace user and provides these data for both on-board and ground-based air traffic control (ATC) services [2, 3]. Multilateration, primary and secondary radars are the main surveillance sensors [4, 5]. Automatic dependent surveillance-broadcast (ADS-B) is a key surveillance element. ADS-B includes airplane position measurement on-board and sharing location with other air space users and ATC.

Measured air traffic data includes noise and multiple gaps, therefore obtained data set is a subject of data processing [6]. Gaps in data are the result of interference or system malfunction [7]. Airplane track identification is an initial step of data processing that collects data related to each airspace user. The second stage includes filtering, track parameters measuring, waypoints identification, and data extrapolation. Obtained data sets are used for the visualization of air traffic for pilots and ATC. Also, track datasets are used to support the safety of air transportation by automatic terrain and mid-air collision detection and avoidance algorithms [8, 9].

Airplane guidance and flight rules depend on the flight phase [10]. There are four main flight phases: taxing, take-off, en-route, and landing. Each phase requires the usage of different equipment and algorithms to support airplane navigation [11]. Therefore, an indication of navigation data for pilots is absolutely different based-on flight phase. The taxing phase includes airplane movement on the ground. Take-off begins from the moment when the vehicle goes from the ground to flying in the air. In the common case, take-off phase includes the whole climbing process up to reach cleared flight level. The en-route phase is usually performed within the network of flight routes at cleared flight level. Most time airplane has constant altitude except for periods of changing flight levels based on ATC clearance. Landing is a final flight phase which may include the whole descending process from cleared flight level up to touch down in runway of the destination airport. Then, taxing at the destination airport facility is used.

Flight phase detection of own airplane and all other airspace users is an important safety task that is performed on both sides of on-board and ground ATC equipment [12, 13]. Time-frame of each flight phase is useful in air traffic delay analysis. Flight phase identification usually grounds on altitude input [14 - 16]. A simple comparison of altitude trends may indicate the flight phase. However, noise action

2022 IEEE 3rd International Conference on System Analysis & Intelligent Computing (SAIC) | 979-8-3503-9674-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/SAIC57818.2022.9922913

during measuring barometrical altitude may significantly degrade the performance of the detector. Therefore, in the paper we study the application of the probability-based approach on the core of the maximum posterior probability method in the task of airplane phase detection. Flight phase identification by maximum posterior probability gives adequate feedback in case of a noisy environment, which reduces the amount of false phase detection.

II. Automatic Dependent Surveillance-Broadcast

Today ADS-B has global coverage. An airplane transponder of 1090ES (extended squitter) mode is the most common on-board equipment that supports ADS-B. The transponder automatically transmits a digital message which includes airplane position. The frequency of this transmission is varied due to personal equipment settings. Data are transmitted via wireless communication channel at 1090MHz in open mode, which makes transmitted data are subject to cybersecurity.

Ground support of ADS-B includes a network of receivers, data decoding, trajectory processing, and archiving equipment. The air navigation service provider is responsible to support ground ADS-B facilities. Network of private software-defined radios located around the world support near the global coverage. Commercially available access to archived surveillance data provided by multiple vendors makes data processing easy for studying aviation safety issues [17]. Also, the constellation of satellite-based receivers of ADS-B is located at the low Earth orbit supports global coverage of all data transmitted over 1090 MHz [18].

Signals transferring at 1090MHz is also used in wide area multilateration that supports the passive method of airplane location measuring.

Data transferred at a 1090MHz channel can be easily received and decoded by software defined radio for air traffic study purposes.

Position report in ADS-B includes actual airplane coordinates in longitude, latitude, and altitude measured by on-board sensors. On-board ADS-B data sensors exchange is represented in Fig.1. Global navigation satellite system (GNSS) is a primary positioning sensor. An inertial navigation system (INS) is used in case of short interruption in the primary positioning system [19]. Poor accuracy of on-board gyroscopes and accelerometers is the main source of INS errors, which are accumulated with a time of INS use. INS provides both lateral positioning and altitude measuring. In the case of both these systems lock an algorithm of positioning by navigational aid initiates in the Flight management system (FMS). In common, positioning by two simulations measured ranges to Distance Measuring Equipment (DME) is automatically initiated within DME covered airspace [20]. Barometric altitude measured by Aid Data System (ADS). FMS includes algorithms of position performance monitoring for each sensor and performs optimal sensor selection to support requirements of navigation specifications [21]. Performance requirements are different for different airspace types and phases of flight in order to guaranty safe airplane separation.

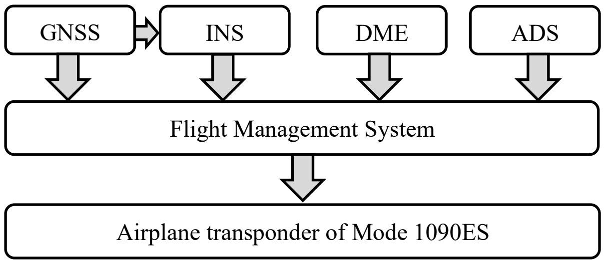

Fig. 1. On-board ADS-B data sensors exchange.

Methods of positioning by pair of DME/DME support only horizontal navigation without altitude data [22]. GNSS and INS support altitude measuring from the ellipsoidal Earth model (Ellipsoid of World Geodetic System WGS84 is commonly used in aviation). The performance of vertical countdown by GNSS is much poorer in comparison with horizontal due to geometrical factor influence.

Barometric altitude is used for airplane leveling by ATC to safe airflow management. Barometric altitude is measured by the dependence of static pressure from altitude [23, 24]. In aviation, barometrical altitude is measured from a standard pressure level of 101.325 kPa which is associated with mean sea level (MSL) at particular conditions [25]. The unique pressure variation gives an identical reference point for altitude measurement and vertical separation between airspace users.

ADS includes specific probes for static pressure (p) measuring. The barometric formula is used to get the current airplane MSL altitude [26]:

- Altitudes up to 11 km

$$H = \frac{T_0}{\tau}\left[1 - \left(\frac{p}{p_0}\right)^{\frac{\tau R}{g}}\right], \tag{1}$$

where p_0, T_0 are standard pressure (101.325 kPa) and temperature (288,15 K); τ= 0,0065 K/m is temperature gradient for troposphere; R=8.314 j/(mol·k) is a universal gas constant.

- Altitudes from 11 to 20 km

$$H = \frac{R}{g}\left[T_T + \frac{(T_0 - T_T)H_T}{2H_{cm}}\right]\ln\frac{p_0}{p}, \tag{2}$$

where H_T, T_T and tropopause altitude (11000 m) and temperature (216.65 K);

- Altitudes from 20 to 32 km

$$H = H_{T+}\frac{T_T}{\tau_c}\left[\left(\frac{p_c}{p}\right)^{\frac{R\tau}{g}} - 1\right], \tag{3}$$

where p_T=22632 Pa is a standard pressure at tropopause level.

Static pressure measuring at altitude from the airframe introduces errors, that are approximately in a range from 0.5% to 1% of the measured value [27, 28]. So big error values require usage statistical data processing in avionics to avoid wrong data usage.

Flight phase identification is mostly grounded on barometrical altitude and vertical speed processing. Therefore, errors in altitude measuring play a significant role in the flight phase identification process.

III. Maximum Posterior Probability Method

The flight phase is a particular state of the airplane which can be represented in a variety of particular parameters. We consider main for phases: taxing, take-off, en-route, and landing. During the flight we do not have data about the current flight phase thus be can introduce hypotheses of particular plight phase appearance: A_1 is a hypothesis of the presence of taxing phase of flight; A_2 is a take-off phase; A_3 is an en-route phase; A_4 is a landing phase.

An airplane can be only in one of these phases at a particular time. Each phase has an equal probability of appearance:

$$P(A_1)=P(A_2)=P(A_3)=P(A_4).$$

All phases compose the full group of evidence:

$$\sum_{i=1}^{N} P(A_i)=1, \quad (4)$$

where N=4 is a number of flight phases.

Posterior probability $P(A/b)$ utilize probability of hypothesis of A includes data b. Posterior probability can be estimated by Bayes formula as follows [29, 30]:

$$P(A_i/b_j)=\frac{P(A_i)P(b_j/A_i)}{\sum_{i=1}^{N} P(A_i)P(b_j/A_i)}, \quad (5)$$

where $P(b/A)$ is a probability b in the condition of evidence A.

Method of maximum posterior probability identify flight phase based on the comparison of the posterior probabilities presence of parameter b at state A. Thus, after getting surveillance data, barometrical altitude can be used to estimate posterior probabilities by (5) and flight phase is identified by maximum probability:

$$q=max\{P(b/A_i),\ i=1,N\}. \quad (6)$$

One of the main advantages of applying this method is that decision is obtained with the minimum risk of false detection. In addition, q represents the probability of correct phase identification. In the common case in detector function (5) a density function $\rho(b/A)$ can be used instead of $P(b/A)$.

As a condition density function $\rho(b/A)$ we use Normal Probability density function:

$$\rho(x)_i=\frac{1}{\sigma_i\sqrt{2\pi}}exp\left(-\frac{(x-\mu_i)}{2\sigma_i^2}\right), \quad (7)$$

where μ is a mean value; σ is mean squared deviation error.

Parameters μ and σ can be estimated based on a learning sample of the previous realization of the same flight or can be tuned to particular properties of the airplane model.

Most flight phases can be easily detected by (5) applying for the parameter of vertical speed, which can be calculated by altitude change between previous and current measuring related to the time between both measurements.

En-route and taxing phases can be classified by taking into account current airplane altitude or geometrical speed. In this case, the bi-variate normal probability density function is useful [31]:

$$\rho_k(x)=\frac{1}{(2\pi)^{K/2}|B_k|^{-1/2}}exp\left[-\frac{1}{2}\left(B_k^{-1}(x-M_k)^T\times(x-M_k)\right)\right], \quad (8)$$

where, $M=[\mu_v,\ \mu_h]$ is a matrix of mean values for vertical speed and altitude; $S=diag([\sigma_v^2,\ \sigma_h^2])$ is a dispersion matrix.

Values of M and S can be estimated from a learning sample in the same way as parameters μ and σ in (7).

IV. Numerical Study

In the numerical study we use raw trajectory data obtained from the national network of ADS-B receivers. We use six-track data in post-processing mode within Ukrainian airspace which includes different geometry configurations. Information about local flights of the input dataset is represented in Table I.

TABLE I. Trajectories data used in flight phase identification

Flight number	Departure airport	Destination airport	Airplane type	Date
WRC117	Boryspil (UKBB)	Ivano-Frankivsk (UKLI)	ATR-72	Jan 04
WRC102D	Dnipro (UKDD)	Boryspil (UKBB)	A 320	Jan 05
WRC165L	Boryspil (UKBB)	Lviv (UKLL)	ATR-72	Jan 04
AUI54	Odesa (UKOO)	Boryspil (UKBB)	B 737	Jan 05
WRC145	Boryspil (UKBB)	Kharkiv (UKHH)	ATR-72	Jan 04
WRC185P	Boryspil (UKBB)	Zaporizhzhia (UKDE)	ATR 72	Jan 03

Flight data is used for the period from 3rd to 5th January 2022. As an example, the flight profile of “WRC145” is presented in Fig. 2. The distribution of total and vertical velocities is represented in Fig. 3.

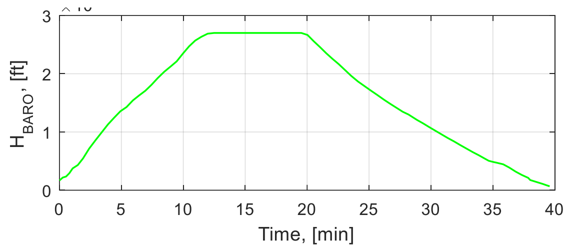

Fig. 2. The altitude of "WRC145".

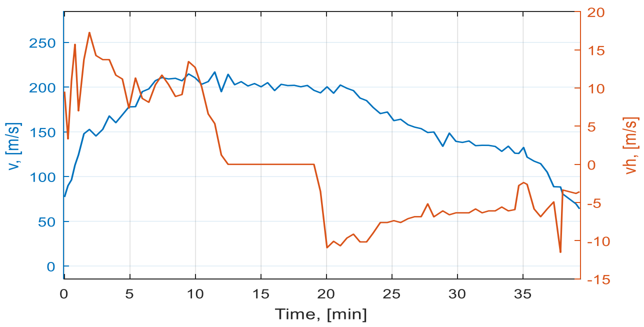

Fig. 3. Total and vertical velocities of "WRC145".

Fig. 2 and Fig. 3 indicate that parameter of verticals barometric velocity is informative enough for phase detection. Thus first 13 min of the flight was in the take-off phase. Then, 13-19 min was en-route and 19-40 was landing. Conditional PDF for each flight phase based on parameter vertical speed is represented in Fig. 4 for "WRC145". The distribution of posterior probabilities estimated by (5) is presented in Fig. 5.

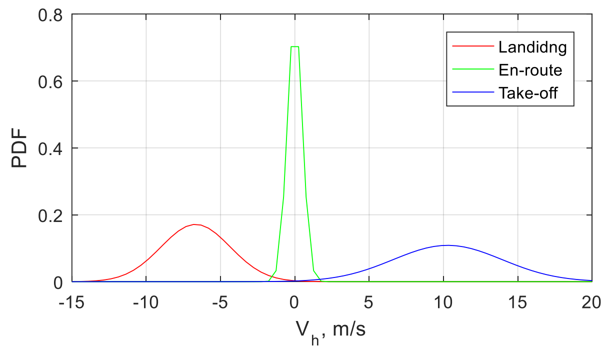

Fig. 4. Conditional PDF for phases of "WRC145".

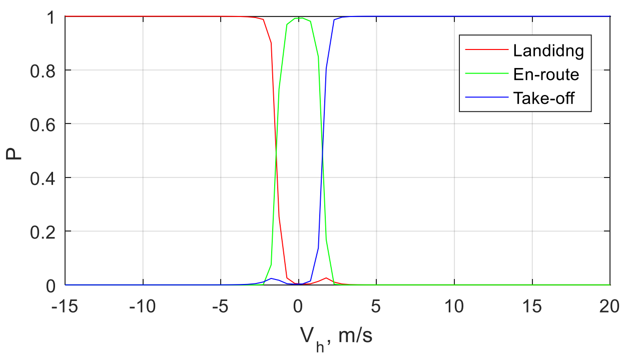

Fig. 5. Posterior probabilities for "WRC145".

Airplane velocity or altitude can be used to get classification between taxing or other phases. Airplane speed is much more useful in this case. Slow speed indicates about taxing phase. Growing speed is normal for take-off, constant speed means en-route, and reducing speed may indicate landing. Thus, we use bi-variate normal probability density function (8) to use geometrical and vertical airplane speeds for phase classification. The posterior probability for bi-variate normal probability density function is represented in Fig.6.

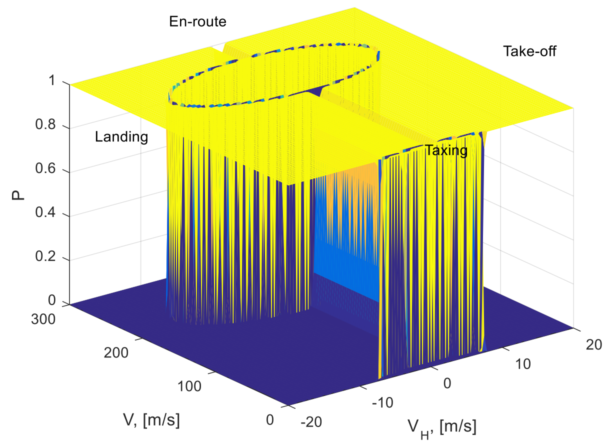

Fig. 6. Posterior probabilities for parameters of geometrical and vertical velocities

Usage airplane geometrical speed as the second informative parameter support exact identification of flight phase. Results of flight phase identification for each point of airplane trajectory cross all data sets are presented in Fig. 7 and Fig. 8, for different planes.

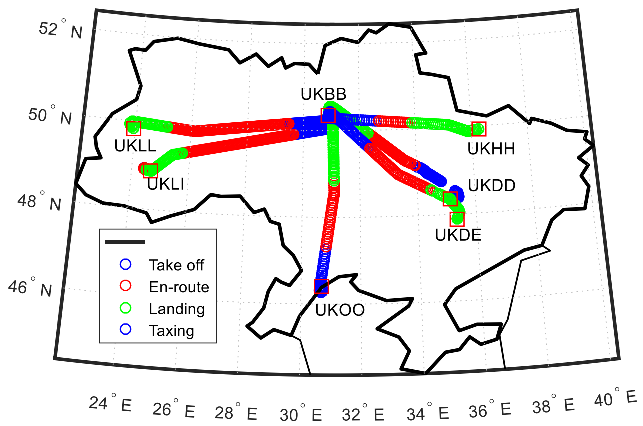

Fig. 7. Results of flight phases identification.

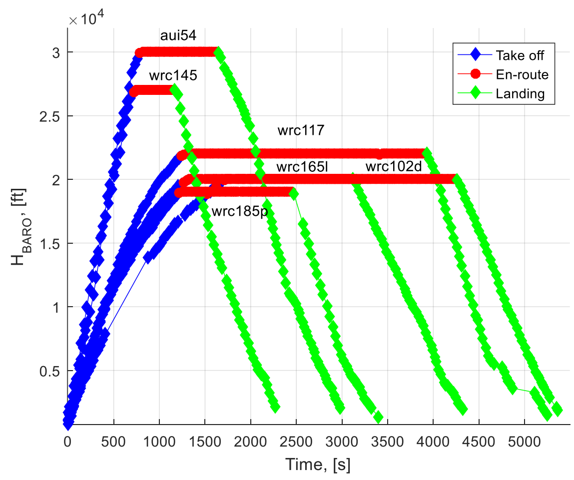

Fig. 8. Results of flight phases identification in vertical plane.

Fig. 8 illustrates vertical profiles of each flight shifted to the time of take-off. Obtained results indicate effective detection even for cases of multiple gaps in the dataset. Gaps in ADS-B data usually are the result of on-board equipment malfunction or interference action in data communication channel. As an example, the gap for "WRC185P" takes more than 6 min (Fig. 8).

CONCLUSIONS

Today trajectory data processing is an important component of surveillance data processing for both on-board and ground sides. Flight phase identification by a maximum of posterior probabilities requires only current and previous vertical speed measured by barometrical sensor or received in ADS-B position report. The main advantage of the probability-based approach includes minimization of errors in measurements, classification with the minimum risk of false detection, and simultaneously available probability of correct decision in the system. Probability of correct decisions is an important input data for probability-based methods of collision avoidance in aviation, which are already been integrated into onboard equipment of aircraft.

Results of practical verification with real trajectory data obtained via ADS-B for Ukrainian airspace give precise detection with low computation power. That makes it possible to use such kind of detector in the structure of on-board flight management system for trajectory data processing.

REFERENCES

[1] Safety Report 2020, International Air Transport Association, Geneva, 2021.

[2] V. Pavlikov, V. Volosyuk, S. Zhyla, H. N. Van, and K. N. Van, "UWB active aperture synthesis radar the operating principle and development of the radar block diagram," IEEE Microwaves, Radar and Remote Sensing Symposium (MRRS), 2017, pp. 27–30.

[3] V. V. Pavlikov, V. K. Volosyuk, and S. S. Zhyla, "Ultra-wideband Passive radars Fundamental Theory and Applications," IEEE 17th International Conference on Mathematical Methods in Electromagnetic Theory (MMET), 2018, pp. 1–6.

[4] Surveillance Radar and Collision Avoidance Systems, Aeronautical Telecommunications, Annex 10. Vol. IV, ICAO, 2018.

[5] V. V. Pavlikov, V. K. Volosyuk, S. S. Zhyla and N. Van Huu, "Active Aperture Synthesis Radar for High Spatial Resolution Imaging," in 9th International Conference on Ultrawideband and Ultrashort Impulse Signals (UWBUSIS), 2018, pp. 252–255.

[6] V. K. Volosyuk, V. V. Pavlikov, and S. S. Zhyla, "Algorithms synthesis and potentiality analysis of optimum ultrawideband signal processing in the radiometric system with modulation," VIII International Conference on Antenna Theory and Techniques, 2011, pp. 235–237.

[7] O. Solomentsev et al., "Method of Optimal Threshold Calculation in Case of Radio Equipment Maintenance," In: S. Shukla, XZ. Gao, J.V. Kureethara, D. Mishra (eds) "Data Science and Security," Lecture Notes in Networks and Systems, Vol 462, 2022, Springer, Singapore, pp. 69–79.

[8] I. Ostroumov and N. Kuzmenko, "Risk Assessment of Mid-air Collision Based on Positioning Performance by Navigational Aids," 2020 IEEE 6th International Conference on Methods and Systems of Navigation and Motion Control (MSNMC), 2020, pp. 34–37, doi: 10.1109/MSNMC50359.2020.9255506.

[9] I.V. Ostroumov, K. Marais, N.S. Kuzmenko, and N. Fala, "Triple Probability Density Distribution model in the task of Aviation Risk Assessment," in Aviation, vol. 24, no. 2, 2020, pp. 57–65 .

[10] K. Kim and I. Hwang, "Intent-based detection and characterization of aircraft maneuvers in en route airspace," in Journal of Aerospace Information Systems. 2018. vol. 15, no. 2, pp. 72–91.

[11] M. Hafidi, M. Benaddy, and S. Krit, "Review of optimization and automation of air traffic control systems," The fourth International Conference on Engineering & MIS 2018. 2018. pp. 1–7.

[12] Q. Zhang, J. H. Mott, M. E. Johnson, and J. A. Springer, "Development of a Reliable Method for General Aviation Flight Phase Identification," in IEEE Transactions on Intelligent Transportation Systems, pp. 1–10.

[13] H. J. Chin, A. Payan, C. Johnson, and D. N. Mavris, "Phases of flight identification for rotorcraft operations," in AIAA Scitech 2019 Forum. 2019. p. 0139.

[14] J. Sun, J. Ellerbroek, and J. Hoekstra, "Large-scale flight phase identification from ads-b data using machine learning methods," 7th International Conference on Research in Air Transportation, 2016. pp. 1–7.

[15] F. Tian, X. Cheng, G. Meng and Y. Xu, "Research on Flight Phase Division Based on Decision Tree Classifier," 2017 2nd IEEE International Conference on Computational Intelligence and Applications (ICCIA), 2017, pp. 372–375.

[16] J. Sun, J. Ellerbroek, and J. Hoekstra, "Flight extraction and phase identification for large automatic dependent surveillance–broadcast datasets," Journal of Aerospace Information Systems, vol. 14, no. 10, pp. 566–572, 2017.

[17] I. Ostroumov and N. Kuzmenko, "Configuration Analysis of European Navigational Aids Network," 2021 Integrated Communications Navigation and Surveillance Conference (ICNS), 2021, pp. 1–9.

[18] M.A. Garcia, J. Stafford, J. Minnix, and J. Dolan, "Aireon space based ADS-B performance model," 2015 Integrated Communication, Navigation and Surveillance Conference (ICNS), 2015, pp. C2-1–C2-10, doi: 10.1109/ICNSURV.2015.7121219.

[19] O. Sushchenko et al., "Design of Robust Control System for Inertially Stabilized Platforms of Ground Vehicles," IEEE EUROCON 2021 - 19th International Conference on Smart Technologies, 2021, pp. 6–10.

[20] N.S. Kuzmenko and I.V. Ostroumov, "Performance Analysis of Positioning System by Navigational Aids in Three Dimensional Space," 2018 IEEE First International Conference on System Analysis & Intelligent Computing (SAIC), 2018, pp. 1–4, doi: 10.1109/SAIC.2018.8516790.

[21] O. Havrylenko, K. Dergachov, V. Pavlikov, S. Zhyla, S., O. Shmatko, N. Ruzhentsev, et al. "Decision Support System Based on the ELECTRE Method," In: S. Shukla, XZ. Gao, J.V. Kureethara, D. Mishra (eds) "Data Science and Security," Lecture Notes in Networks and Systems, Vol 462, 2022, Springer, Singapore, pp. 295–304

[22] I.V. Ostroumov, N.S. Kuzmenko and K. Marais, "Optimal Pair of Navigational Aids Selection," 2018 IEEE 5th International Conference on Methods and Systems of Navigation and Motion Control (MSNMC), 2018, pp. 32–35.

[23] H.A Hernandez, "Barometric Formula without the Hydrostatic Pressure Assumption," in ForsChem Research Reports. 2020. Vol. 5. pp. 1–22.

[24] M.N. Berberan-Santos, E.N. Bodunov, and L. Pogliani, "On the barometric formula," in American Journal of Physics, vol. 65, no. 5, pp. 404–412, 1997.

[25] Manual of the ICAO Standard Atmosphere, Doc 7488, ICAO, 1993.

[26] T.L. Grigorie, L. Dinca, J.I. Corcau, and O. Grigorie, "Aircrafts' altitude measurement using pressure information: barometric altitude and density altitude," Wseas transactions on circuits and systems, vol. 9, issue 7, 2010, pp. 503–512.

[27] A.R. Rodi and D.C. Leon, "Correction of static pressure on a research aircraft in accelerated flight using differential pressure measurements," Atmospheric Measurement Techniques, vol. 5, issue 11, 2012. pp. 2569–2579.

[28] D.A. Reasor, K.K. Bhamidipati, and R.K. Woolf, "Numerical Predictions of Static-Pressure-Error Corrections for a Modified T-38C Aircraft," Journal of Aircraft, vol. 52, issue 4, 2015. pp. 1326–1335.

[29] B.M. Steele, "Maximum posterior probability estimators of map accuracy," Remote Sensing of Environment. 2005. vol. 99, no. 3. pp. 254–270.

[30] M.N. Murty and V.S. Devi, "Bayes classifier," in Pattern Recognition. Springer, 2011. pp. 86–102.

[31] N.T. Thomopoulos, Probability Distributions. Springer. 2018. doi: 10.1007/978-3-319-76042-1.