

The object of this study is the process of forming a training dataset for diagnosing the technical condition of unmanned aerial vehicles (UAVs) using machine-learning algorithms. UAV flights are extremely important for various aspects of troop deployment. Combat UAV flights are performed under the influence of negative factors that cause flight special cases (FSC), which hinder the execution of combat missions, lead to mission failures, and result in the aircraft damage or loss. The available capabilities of autopilots are not enough for control under complex conditions, and in certain situations, the human operator cannot timely recognize a flight special case, including evaluation of the destructive impact of enemy's electronic warfare systems on communication channels and operation of UAV. Therefore, the urgent issue is the intellectualization of onboard control systems, particularly towards recognizing the current technical state of UAV using artificial intelligence methods. To design such systems, labeled datasets are required. The procedure for forming datasets that consider the specificity of UAV construction and their combat use under adversarial conditions is not defined, necessitating the development of an appropriate method.

Based on the well-known CRISP-DM methodology, a method for dataset formation has been proposed for subsequent use in artificial intelligence systems that use various machine-learning methods.

This method differs from existing ones by considering the specificity of combat mission execution under adversarial conditions, which allowed for an 8.0 % increase in the accuracy of recognizing special cases in UAV flights by the onboard system. It also enabled timely detection of electronic warfare impacts on UAV and evaluation of the effectiveness of radio signal receivers jamming

Keywords: *unmanned aerial vehicle, training dataset, machine learning, jamming effectiveness evaluation*

UDC 629.7:004.8

DOI: 10.15587/1729-4061.2024.312217

DEVISING A METHOD FOR INTEGRATED DATASET FORMATION AND SELECTING A MODEL FOR RECOGNIZING THE TECHNICAL CONDITION OF UNMANNED AERIAL VEHICLE

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Received date 30.07.2024

Accepted date 18.10.2024

Published date 30.10.2024

How to Cite: Perehuda, O., Rodionov, A., Fedorchuk, D., Zhuravskyi, S., Konvisar, M., Volynets, T., Datsyk, V., Zakalad, M., Tsybulia, S., Trysnyuk, T. (2024). Devising a method for integrated dataset formation and selecting a model for recognizing the technical condition of unmanned aerial vehicle. *Eastern-European Journal of Enterprise Technologies*, 5 (4 (131)), 42–51. <https://doi.org/10.15587/1729-4061.2024.312217>

1. Introduction

The experience of protecting Ukraine from the armed aggression of the Russian Federation has shown that unmanned aerial vehicles play an important role both in receiving intelligence information and in maintaining artillery fire and inflict-

ing damage on the enemy. Unmanned aerial systems (UASs) are most widely used in the military, the aircraft of which, according to the current documents of the Ministry of Defense, are class I UAVs. Combat tasks with the use of Class I UAVs are carried out under conditions of countermeasures, including the use of radio-electronic warfare, which are characterized

by suddenness and deliberate use. This greatly affects the performance of combat tasks and can lead to undesirable consequences. Among them is a decrease in the effectiveness of the functioning of UAVs (UASs), a decrease in the quality of task performance, or even their breakdowns: cases of damage to aircraft and their loss [1, 2].

Analysis of modern world trends in the development of UAVs [3–14] reveals a tendency to increase the level of intellectualization of on-board control systems to ensure the performance of complex tasks entrusted to them. Various methods of artificial intelligence are used for this purpose.

A relevant area of the intellectualization of airborne control systems is the recognition of the current technical state of UAVs and the detection of external influences on UAVs, for example, to evaluate the effectiveness of radio suppression of radio signal receivers of airborne radio systems. Subsequently, the current technical state refers to a set of states of normal functioning or to a certain state from a set of states characterized by the presence of FSC. When states from the second set are detected, appropriate measures are taken to increase the survivability of UAVs. FSC is a situation that occurs in flight because of the influence of dangerous factors.

Determining the technical condition of Class I UAVs caused by enemy countermeasures, including evaluating the effectiveness of this effect in terms of radio suppression of receivers of onboard radio systems, is a challenging task. It is complicated by the lack of a mathematical model that would take into account the parameters of the environment, the different effects of the enemy's electronic warfare equipment on the on-board receivers of various types of UAVs. Therefore, artificial intelligence methods could be used to solve such scientific tasks.

The implementation of some methods is based on the training of systems with elements of artificial intelligence on pre-marked data (samples). This makes it possible to model the cognitive processes that are inherent in a person when making decisions about the absence or presence of FSC and determining its type. To obtain a quality model, the algorithms require a significant amount of labeled data for each class in the training phase. Therefore, it is relevant to devise an approach to forming samples for solving the tasks of recognizing the current technical state of UAVs using systems with elements of artificial intelligence. Such systems could also perform other tasks: detect human operator errors, malfunctions of specific sensors, pre-accident states of UAVs, predict UAV movement parameters, evaluate the effectiveness of radio suppression of receivers of on-board radio systems.

2. Literature review and problem statement

Systems with elements of artificial intelligence have demonstrated the ability to solve a wide range of both scientific and engineering tasks. In various directions, the issue of intellectualization of airborne systems of UAVs is considered by scientists in many works. In [3, 4], the recognition of the fact of cybernetic attacks in UAV communication lines is considered. The disadvantage of these works is that the research is carried out using exclusively commercially available UAVs, the peculiarities of the organization of communication in military UAVs are not taken into account. In addition, according to the experience of using UAVs during the defense of Ukraine, a more urgent issue is the detection of the fact of radio-electronic suppression of on-board receivers.

Examples of systems that recognize the suppression of satellite navigation system signal receivers and interference in the communication lines of commercial UAVs are considered in [5, 6], respectively. However, the authors focus on the solution of these specific tasks, and therefore, these advancements do not allow for a comprehensive assessment of the technical condition of UAVs in the event of other situations.

Systems for recognizing the technical condition of UAVs, based on rules, are considered in [7, 8]. The authors consider the possibilities of unauthorized interference in the UAV communication line. The advantage of the proposed approaches is a fairly high accuracy of situation recognition. Among the shortcomings of these systems, rather high complexity and the impossibility of detecting out-of-state situations that are not modeled by the rules are noted.

At the same time, approaches based on data analysis, in which the system model is built using available a priori data about its states, are gaining popularity [9, 10]. In particular, paper [9] studies the training of a system with elements of artificial intelligence to determine propeller damage, their imbalance, and engine failure for multicopter-type UAVs, and study [10] uses principal component data analysis to detect certain failures. The main focus of the authors is on setting up the models. However, the tasks are solved for a limited number of situations, and the issue of obtaining (forming) samples is not considered.

Recognition of the technical condition is also considered in a rather limited way in [11–13]. In [11], the author considers the possibility of training generative competitive networks in classifying the technical state of UAVs as normal or abnormal, but other categories are not considered, which makes it impossible to determine the type of emergency situation.

Artificial neural networks and the method of support vectors (Support Vector Machine – SVM) are used in [12]. The advantages of the proposed approach are that the authors take into account possible changes in UAV flight conditions, and certain transformations are performed on the training dataset. However, the essence of the operation on the training dataset is not disclosed, the procedure for obtaining it is not specified.

The authors of [13] use a sample of current and voltage values of multicopter UAV engines and train algorithms that implement logistic regression and discriminant analysis. However, out of the multitude of all possible non-standard situations, only one is considered, the training dataset contains data exclusively for this specific task.

In paper [14], the use of convolutional neural networks is proposed to recognize out-of-state situations. In this way, failures of the engine and aerodynamic controls are recognized, but the indicated situations reflect internal failures, so they are not related to a possible external intentional influence. The procedure for obtaining samples for setting up convolutional neural networks is not considered at all.

Our review reveals that considerable attention of scientists is devoted to the use of approaches based on data analysis. There are many algorithms that use samples for learning and setting up systems with elements of artificial intelligence to solve this class of problems.

At the same time, the authors of the above scientific works solve specific tasks, limiting themselves to only a certain set of situations, the specificity of the use of UAVs in the military sphere under conditions of deliberate influence are not considered. At the same time, the issue of formation of training datasets is not covered in these works or is considered superficially in each case specifically for the current task.

This outlines an unresolved issue in the scientific literature: the lack of methods for forming training datasets for use in research on recognizing the technical condition of UAVs because of the influence of various factors.

3. The aim and objectives of the study

The purpose of our study is to devise a method for building training datasets to set up systems for recognizing the technical condition of Class I UAVs during combat missions. This will make it possible to form training datasets to design systems for recognizing the current state of UAVs. Such systems as part of the on-board control equipment will make it possible to increase the effectiveness of combat missions, improve the survivability of UAVs, and reduce aircraft losses during combat use. In addition, it is possible to use the obtained samples to solve other scientific tasks in the specific field of application of UAVs.

To achieve the goal, it is necessary to solve the following tasks:

- to propose a conceptual solution regarding the method for constructing a training dataset and the algorithm of its implementation;
- to evaluate the effectiveness of various machine learning algorithms when using the resulting dataset.

4. The study materials and methods

The object of our study is the process of forming a training dataset for diagnosing the technical condition of UAVs. The research hypothesis assumes that with the use of machine learning algorithms it could be possible to simulate the cognitive processes inherent in a person when making decisions about the presence of FSC and its type.

There is a fairly large number of different types of FSCs that can occur during the combat use of UAVs, so the recognition process is considered with certain simplifications and assumptions. The study examines a simplified set of FSCs that occur during the flight of UAVs (without distinguishing the stages of the flight) and are associated with the influence of negative factors, including intentional ones created by the enemy. It is assumed that all elements of on-board equipment are technically functional, means of fire damage to UAVs (or other kinetic effects) are not used by the enemy. Therefore, FSCs related to accidental failures of UAV equipment elements and mechanical damage are not considered.

Extraction of parameters from log files is carried out taking into account the principle of data storage by the names of the corresponding fields and attributes and is automated by a parser in the Python programming language.

Further data processing involves the use of outlier filtering methods, expert methods for data labeling, and methods for solving the problem of unbalanced data.

Different machine learning algorithms are used to train models for recognizing the technical condition of UAVs based on the resulting dataset.

A typical first-class UAV is under consideration. Let it be an aircraft-type UAV with a "flying wing" aerodynamic scheme, built on the basis of an autopilot (flight controller) of the PixHawk family. The characteristics of the autopilot and the algorithms of its functioning are known. The UAV is equipped with a command and telemetry channel (CTC) and

a satellite navigation system (SNA) signal receiver, which are necessary for flight performance.

The command-telemetry radio channel technically combines:

- command radio channel – intended for transmission of control signals from the control point to the on-board equipment of UAV, which processes the received control commands. According to these commands, the UAV changes flight modes, altitude, course, speed, operation modes of the target load, performs maneuvers;

- the telemetry channel is intended for the transmission of receipts for the execution of commands received on board, the transmission of signals from on-board sensors regarding the technical condition of on-board equipment and the environment (flight conditions).

The SNS signal receiver receives signals from such systems as GPS, GLONASS, Galileo, Baidu.

Let there be a set of states $S=\{s_i\}$, $i=1,\bar{I}$, in which UAV can be; the set of states that characterize the normal functioning $S_j^1=\{s_1^1, s_2^1, \dots, s_j^1\}=\{s_j^1\}$, $j=1,\bar{J}$; the set of states that characterize the functioning of UAV in the event of FSC $S_n^2=\{s_1^2, s_2^2, \dots, s_n^2\}=\{s_n^2\}$, $n=1,\bar{N}$, N is the number of states characterized by FSC (by the number of FSCs), and $S^1 \cup S^2 = S$, $S^1 \cap S^2 = \{\}$.

Let there be a certain collection of observations in the form of a flight log file. A log file is a file of a certain structure in which the values of a significant number of various technical parameters characterizing the state of UAV are recorded. Among them are flight mode, on-board battery voltage value, current consumption, indicators of gyroscopes and accelerometers, barometric sensor, data from receivers of the satellite navigation system and from all additional devices connected to the autopilot.

It is known that during the flight of UAV, two log files are built: one on board the UAV, the second at the remote piloting point (RPP). The first of these contains a larger number of parameters, the second registers the parameters received by the RPP software.

The log files contain a significant number of parameters and their values at different time points during the flight. In the theory of data processing, such data are termed "raw data", i.e., data that require further processing.

In the study, entries in the log file were considered as a set $X_{raw}=\{x_{raw_n}^m\}$, where $m=1, \bar{M}$ – the number of log file entries at different points in time, $n=1, \bar{N}$ – the number of parameters recorded at a certain point in time.

For example, for the on-board log file of the PixHawk flight controller, a flight lasting 60 minutes $X_{raw_b}=\{x_{raw_{b_n}}^m\}$ contains the number of records at different time points $m=2,611,538$; the number of fields for recording parameters $n=363$ (the number of recorded parameters may be different depending on the configuration of the on-board equipment). Obviously, the data represented in X_{raw_b} to get the sample needs processing.

Sources of data from UAVs for further processing can be log files received:

- based on the results of training and combat flights, which are carried out by training units and units of UAS military units of various types and types of troops;
- by software simulation of UAV flight in specialized software environments.

Each approach has advantages and disadvantages but the choice and justification of a particular one of them is a separate area of research and is not considered within the framework of this work.

FSCs and their classification, adapted to the realities of modern application of UAS, taking into account the current governing documents, are given in [15].

5. Results of devising a method for integrated formation of a dataset to recognize the technical condition of an unmanned aerial vehicle

5.1. Development of a conceptual solution regarding the method for forming the training dataset and the algorithm of its implementation

To solve this task, a set of transformations of "raw" data is proposed to obtain a high-quality training dataset, suitable for use in systems with elements of artificial intelligence that use machine learning algorithms. The construction of the method is based on the general CRISP-DM methodology (Cross-industry standard process for data mining), the most common methodology for processing data intended for use in the field of machine learning [16, 17]. It is considered as a process model that describes the basic approaches used by experts in the field of machine learning to obtain data and can be adapted by researchers depending on the field of application [18–21]. Based on the analysis of this methodology, the synthesis of the method was carried out and the algorithm for its implementation was developed. Each of the stages is adapted to the solved task and features in the construction of the class I UAV.

The stages of data processing are aimed at obtaining a sample $A = \{X, S\}$ for use in systems with elements of artificial intelligence, which implement various approaches based on data analysis to solve the task of recognizing the current technical state of UAVs.

The sample consists of k instances $X = \{x_k\}$, $k = 1, \bar{K}$ and each instance is characterized by a certain set of features $x_k = \{p_{k1}, p_{k2}, \dots, p_{kj}\}$, $j = 1, \bar{J}$ is the number of attributes that characterize the sample instances. The instances are matched with the values of the original attribute $S = \{s_k\}$, where k is the number of the corresponding instance of the sample. For the task of recognizing the technical state of UAVs, Q states are defined, which are essentially classes to be recognized. Thus, each individual k -th precedent can be represented as $\langle x_k, s_k \rangle$, $x_k = \{p_{kj}\}$, $s_k \in \{1, 2, \dots, Q\}$, $Q > 1$. According to the results of the research and analysis of the stages of the CRISP-DM methodology [16, 17], a conceptual solution regarding the method of forming the training dataset and the algorithm for its implementation is proposed. The solution implements a set of techniques of transformation of available data and procedures for researching their characteristics to obtain the best performance of models trained on the received sample.

Using these samples, such systems can recognize the technical condition of Class I UAVs and perform other tasks, such as evaluating the effectiveness of radio suppression of UAV receivers.

The implementation algorithm of the above method involves four stages, each of which contains the corresponding steps. The stages and steps are typical but depending on the specificity of the task and the technologies used to solve it, they can be adapted. Their content is as follows:

1. Analysis of the subject area. Defining the list of controlled parameters.

At this stage, the flight parameters are analyzed, the change of which indicates changes in the state of UAV. The task of classifying the current technical state of UAV models the cognitive processes inherent in a person when making

a decision. It is necessary to define a list of FSCs that are subject to recognition, each FSC will represent one of the classes from Q . For each FSC, an analysis of parameters is performed, based on which (by a combination of which) the external pilot-operator makes a decision about the presence or absence of FSC and determines which FSC is observed at the moment. If there is sufficient knowledge about the principles of system operation, the list of controlled parameters also includes parameters that are not visible to the human operator but are useful for analysis. A detailed analysis ensures the compliance of the selected controlled parameters (characteristics) with the problem to be solved:

$$P_k = \left\{ P_{s_n^2} \left| \begin{array}{l} n \geq 1; \forall P_{s_n^2} \neq \emptyset; \exists P_{s_m^2}, P_{s_k^2}, \\ m \neq k, 1 \leq m, k \leq N, P_{s_m^2} \neq P_{s_k^2} \end{array} \right. \right\}, P_k \subseteq P, \quad (1)$$

where P is a set of all UAV parameters; P_k is a set of controlled UAV parameters; $P_{s_n^2} = \{p_{1s_n^2}, p_{2s_n^2}, \dots, p_{q_{ns_n^2}}\}$ – a set of parameters that characterize the state of the UAV in FSC s_n^2 , $n = 1..N$ – the number of states in FSC that are subject to consideration (analysis), q_n – the number of change parameters that characterize the state s_n^2 in FSC.

2. Primary data analysis.

2.1. Data collection – extraction of parameters from the log file.

Records of the necessary controlled parameters are extracted from the entire set of parameters recorded in the log file:

$$X_{sel} = \left\{ x_{seli} \left| x_{seli} = \{p_{ij} \mid p_{ij} \in P_k\}, x_{rawi} \in X_{raw} \right. \right\}, \quad (2)$$

where X_{sel} is the data set obtained as a result of extraction, $X_{sel} = \{x_{sel1}, x_{sel2}, \dots, x_{selI}\}$, which is a set of I records, each of which contains J parameters $x_{seli} = \{p_{seli1}, p_{seli2}, \dots, p_{seliJ}\}$; $X_{raw} = \{x_{raw1}, x_{raw2}, \dots, x_{rawn}\}$ is a set of n records in the log file, each record contains m parameters $x_{rawn} = \{p_{n1}, p_{n2}, \dots, p_{nm}\}$.

Extraction is carried out by the names of the corresponding data fields in the log file. Manual processing of large-dimensional data is a long and complex process, therefore, for this purpose, a parser in the Python programming language was developed, which, based on the names of attributes and fields, receives a set of records of relevant parameters. Data collection can be carried out from several sources (log files) if necessary. When using multiple log files, it is necessary to integrate the data to obtain a single data set suitable for use as a sample. Integration for convenience can be carried out after completion of other stages.

2.2. Bringing the obtained parameters to a single sampling frequency.

Different attributes from the list of monitored parameters can have different sampling rates. So, for example, for Pix-Hawk, the sampling frequency of the parameters characterizing the communication status is 25 Hz, the indicators of the air speed sensor are 10 Hz, and some parameters of the navigation system are 5 Hz. Therefore, in one time interval, the number of records for different parameters will be different, which makes it necessary to bring the parameters to a single frequency:

$$\begin{aligned} \exists p_{ij} \in x_{seli} : f_{p_{ij}} &\neq f_{p_{i+1j}}, \\ F : X_{sel} \{x_{seli}\} &\rightarrow X_f \{x_{fi} \mid \forall f_{p_{ij}} = f_{p_{i+1j}}\}, \end{aligned} \quad (3)$$

where $x_{fi} = \{p_{fi1}, p_{fi2}, \dots, p_{fiJ}\}$, $X_f = \{x_{fi}\}$ is a data set with parameters reduced to a single sampling frequency.

3. Data preparation. According to [22], it is the most time-consuming stage, which aims to prepare a training data-set for use in simulation.

3.1. Filtering of missing, repeated, and anomalous values (outliers) [23].

Instances in which one or more values are missing and instances that contain the same values of controlled parameters are deleted from the existing data array.

Formally, the following relations describe the steps:

– filtering of missing data forms a data set:

$$X_{null} = \{x_{f_i} \in X_f \mid \forall j (p_{ij} \neq null)\}, \quad (4)$$

with corresponding elements $X_{null} = \{x_{null1}, x_{null2}, \dots, x_{nullI'}\}$, $I' \leq I$;

– filtering of duplicate data:

$$X_{rep} = \{x_{nulli'} \in X_{null} \mid \forall x_{nullm}, 1 \leq m \leq I', 1 \leq n, m \leq I'\}, \quad (5)$$

with corresponding elements $X_{rep} = \{x_{rep1}, x_{rep2}, \dots, x_{repI''}\}$, $I'' \leq I'$.

To increase the level of reliability of information, anomalous values (outliers) are searched for and removed from the data set. Using the Z-score method (standard observation score), formalized filtering of anomalous values (outliers) is represented as:

$$X_{anom} = \{x_{repi''} \in X_{rep} \mid \forall j (|p_{repi''j} - \mu_j| \leq k\sigma_j), p_{repi''j} \in x_{repi''}\}, \quad (6)$$

with elements $X_{anom} = \{x_{anom1}, x_{anom2}, \dots, x_{anomI'''}\}$, $I''' \leq I''$, where

$\mu_j = \frac{1}{I'''} \sum_{i=1}^{I'''} p_{repi''j}$ is the average value of the j -th parameter $p_{repi''j} \in x_{repi''}$; $\sigma_j = \sqrt{\frac{1}{I'''} \sum_{i=1}^{I'''} (p_{repi''j} - \mu_j)^2}$; k is the number of standard deviations that determines the limit of normality.

3.2. Data formatting – conversion of dimensions of controlled parameters from raw data into dimensions perceived by a person (if necessary – calculation of certain values). Various attributes from the list of controlled parameters in the log file may have dimensions of values that are difficult for a person to perceive and must be transformed in a certain way:

$$X_{form} = \left\{ x_{formi''''j} \mid \begin{aligned} &x_{formi''''j} = \\ &= \{p_{anom i''''j} \mid k \notin C\} \cup \\ &\cup \{p'_{anom i''''j} \mid j \in C\} \end{aligned} \right\}, \quad (7)$$

where $X_{form} = \{x_{form1j}, x_{form2j}, \dots, x_{formI''''j}\}$ is a data set with corresponding elements obtained as a result of formatting; $C = \langle 1, 2, \dots, m \rangle$ – a tuple of indices of parameters that require conversion; $p'_{anom i''''j} = T_j(p_{anom i''''j})$, $j \in C$ is the converted j -th parameter of the corresponding record from the sample obtained in the previous step; T_j is the conversion function of parameter p_j .

Examples for PixHawk are the values obtained from the barometric sensor and given in Pa – for a person to understand the flight height, these values are calculated according to the appropriate formulas in meters.

3.3. Marking of data.

To ensure the operation of learning algorithms, a priori information is needed regarding the belonging of sample instances to the original attribute. To implement this step, the above algorithm suggests the involvement of experts familiar with the operation of a specific UAV for which the task of recognizing the technical condition will be solved. Experts

determine the belonging of each instance of the sample to the appropriate class, which characterizes the state of UAV in FSC:

$$E: X_{form} \rightarrow A\{X, S^E\}, \quad (8)$$

where $X = \{x_k\}$, $k = 1, \bar{K}$ is a set of instances in the sample, each of which contains a set of parameters $x_k = \{p_{k1}, p_{k2}, \dots, p_{kK}\}$; $S^E = \{s_k\}$, $S^E \subseteq S^2$ – the set of states determined by experts for each x_k of the $q = 1, \bar{Q}$ number of states; E is some function that reflects expert processing.

It is proposed to implement this in an interface identical to the software interface of the real RPP of a specific UAS.

3.4. Checking for data balance and generation of training datasets evenly distributed across classes.

To ensure the uniformity of data distribution in the sample, it includes data describing each of the defined classes in equal parts [24]:

$$\begin{aligned} A_{eq}\{X, S^E\} = \\ = \{x_k, s_k\} \mid A_{eq}\{X, S^E\} : \forall q (P(q) \approx P(q+1)), R_g' \rightarrow 0, \end{aligned} \quad (9)$$

where $P(q) = S^{2q}/K$, $q = 1, \bar{Q}$, where S^q is the number of instances of the sample that belong to the q -th class, $P(q)$ is the estimate of the a priori probability (frequency) of the

q -th class in the sample; $R_g' = \frac{1}{K} \sqrt{\sum_{q=1}^Q \left(S^{2q} - \frac{1}{Q} \sum_{q=1}^Q S^{2q} \right)^2}$ is a relative characteristic of the unevenness of the training dataset, $R_g' = [0, 1]$.

As a rule, the uniform distribution of sample instances by classes is possible due to the availability of a large amount of data obtained from log files at previous stages.

If it is impossible to carry out an uneven distribution of the sample by classes, approaches to solving the problem of unbalanced classes can be additionally applied, for example: methods based on boosting algorithms, methods based on the duplication of objects of the minority class, methods based on the removal of objects of the majority class, methods based on neural networks [25, 26].

Thus, formally, the steps of this stage consist of successive transformations of previously obtained data:

$$X_{null} \rightarrow X_{rep} \rightarrow X_{anom} \rightarrow X_{form} \rightarrow A\{X, S^E\} \rightarrow A_{eq}\{X, S^E\}.$$

4. Modeling.

4.1. Selection of models for training systems with elements of artificial intelligence to recognize the technical condition of UAVs.

Various models for solving the task of recognizing UAV states are considered and evaluated according to certain criteria for further use:

$$M^* = \left\{ m_i \mid \arg \max_{c=1}^C (m_i) \geq \varphi \right\}, M^* \subseteq M, \quad (10)$$

where $M = \{m_i\}$ is the set of models under consideration, $c = 1, \bar{C}$ is the set of model quality assessment criteria, φ is the limit value of the general quality criterion, M^* is the set of models selected for further work.

Examples of such models to be considered: decision trees, the support vector machine (SVM), neural networks, gradient boosting (Gradient Boosting Machines), the K-Nearest Neighbors method, and others.

4. 2. Training and setting the parameters of the selected models.

Depending on the algorithms selected for simulation, their characteristic parameters are adjusted:

$$\forall m_i^* \in M^*,$$

$$m_i^*(\theta_i) \xrightarrow{F} m_i^*(\theta_i^*) \mid \theta_i^* = \arg \max_{\theta_i} T(m_i^*, \theta_i), \quad (11)$$

where $m_i^*(\theta_i)$ is the i -th model from the set M^* with its corresponding setting parameters $\theta_i = \{\theta_{i1}, \theta_{i2}, \dots, \theta_{ik}\}$, k is the number of model parameters m_i^* ; F is a certain function that reflects the mechanism of setting the parameters of a specific model; $T(m_i^*, \theta_i)$ is the function of estimating the accuracy of the model m_i^* for parameters θ_i ; θ_i^* is the value of a set of parameters for which $T(m_i^*, \theta_i^*) = T_{\max}$.

Among the parameters that can be adjusted for different models are the maximum depth of the decision tree, the number of layers and neurons for neural networks, regularization parameters for SVM, etc. This step can be performed iteratively.

4. 3. Evaluation of results.

It involves defining the metrics for evaluating models: accuracy, sensitivity, specificity, F1-score, ROC-AUC for recognition of UAV states. After that, the models are tested on a test sample or on new data, their effectiveness is evaluated

according to the selected metrics, to determine the model that allows solving the task with the greatest efficiency:

$$m^* = \arg \max_{i=1}^I f(m_i^*), \quad (12)$$

where m^* is a model that is the result of a choice among I models based on the value of a certain evaluation function $f(m_i^*)$. If $f(m_i^*)$ has the form of a scalar convolution,

then $m^* = \arg \max_{i=1}^I \sum_{j=1}^J \alpha_j C_{mj}(m_i^*)$, $\sum_{j=1}^J \alpha_j = 1$, $\alpha_j \geq 0$, where C_{mj} ,

$j=1, J$ is a set of criteria that reflects the metrics selected for evaluation, $C_{mj}(m_i^*)$ is the value of j -th criterion for the i -th model, α_j is the weight coefficient of the j -th criterion.

At the same time, the utility function $f(m^*)$ of the best model m^* must satisfy the requirement $f(m^*) \geq f'(m^*)$, where $f'(m^*)$ is a given (required) value. Otherwise, the CRISP-DM methodology involves returning to stages 3. Data preparation or to stage 1. Domain analysis and repeating all subsequent actions.

Thus, the application of the method makes it possible to obtain an unrepeatable, class-balanced sample, in which there are no missing or anomalous values.

The block diagram of the algorithm for the transformation process of available data is shown in Fig. 1.

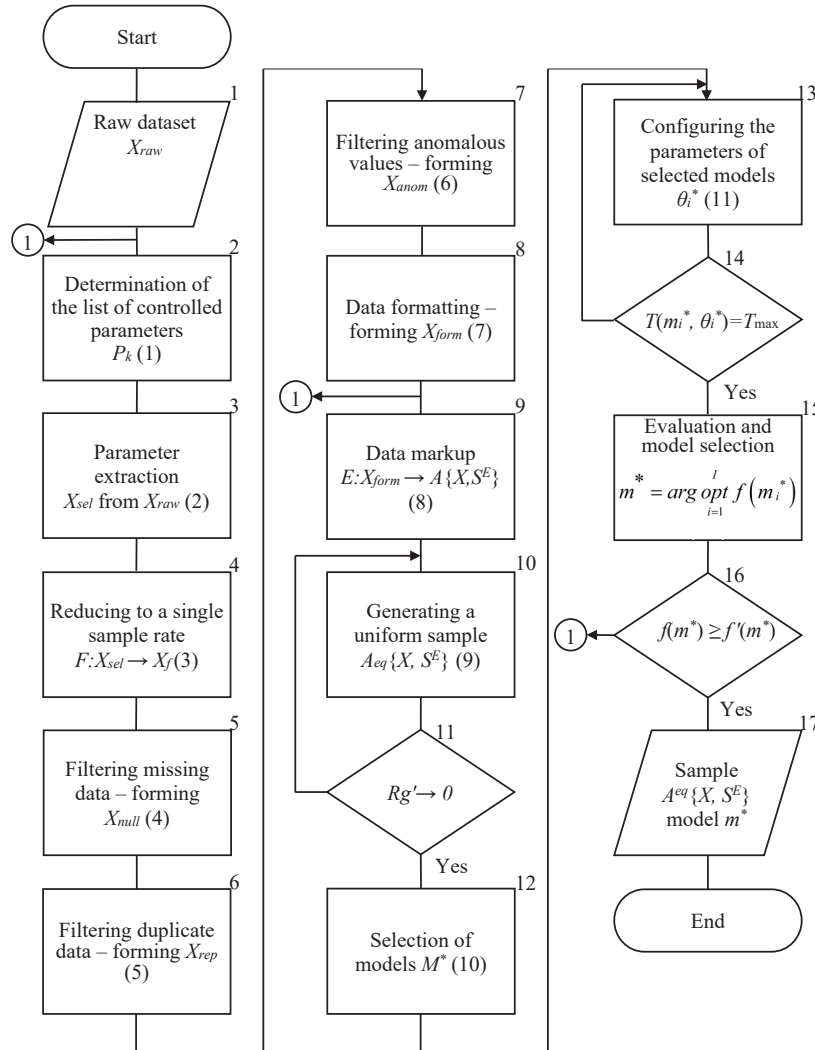


Fig. 1. Algorithm of the transformation process of available data for forming a sample and choosing a model for recognizing the technical condition of an unmanned aerial vehicle

The block diagram of the algorithm shows the sequence of steps of the proposed method and the connections between them.

5.2. Evaluating the effectiveness of different machine learning algorithms when using the resulting dataset, model selection.

An experiment was conducted to check the efficiency of the algorithm and evaluate its performance. The purpose of the experiment is to check the effectiveness of the algorithm for forming samples for recognizing the technical condition of UAVs, as well as its universality – the possibility of using the received data in systems with elements of artificial intelligence that are implemented using various technologies.

The simplest option is binary classification, but it is not appropriate for the problem being solved. Based on the experience of using Class I UAVs during combat missions, we shall consider an example of assigning the UAV technical state to one of three classes ($Q=3$): normal flight state, state of suppression of the on-board CTK receiver, state of suppression of the on-board SNS receiver, respectively. Data extraction is carried out using the appropriate script, their processing and evaluation of classifiers – in the specialized MATLAB software environment:

1. Analysis of the subject area. An analysis of the activity of the human operator was carried out when deciding on the presence of the specified special cases:

- the state of suppression of the CTC on-board receiver is recognized by the operator through the value of the communication level indicator, due to delays in updating telemetry data;
- the state of suppression of SNS signals is recognized by the small number of satellites from which the signal is received or in their absence, incorrect positioning of UAV compared to the one determined by the operator based on visual landmarks;
- the state of normal flight is characterized by the values of the above-mentioned indicators, which are within the normal limits.

The first stage (analysis of the subject area) of the algorithm for the implementation of the specified method provides for the possibility of including in the list of controlled parameters also parameters that are not displayed to the human operator but are useful for the analysis. Accordingly, understanding the principles of operation of the first-class UAV SNS, we shall include an additional parameter – positioning accuracy in the horizontal plane – to the list of controlled parameters.

2. Data extraction is performed by attribute and field names:

- for the communication level indicator: attribute – RSSI, field – RxRSSI (RSSI.RxRSSI);
- for the number of satellites: attribute GPS, field – NSats (GPS.NSats);
- for positioning accuracy in the horizontal plane: GPS attribute, field – HDop (GPS.HDop).

Data sources are two log files: both of them contain records of the technical state of normal flight; at the same time, the first contains records of suppression (obstacles) of CTC, the second – suppression of SNS signals.

For ease of processing, data extraction was carried out at time intervals that correspond to the corresponding states in three data sets.

After carrying out stages 2.1–3.3, three data sets of different dimensions were obtained, which make up the sample.

The a priori distribution of probabilities of the q -th class for the sample was: $P(q=1)=0.5157$; $P(q=2)=0.4736$; $P(q=3)=0.0105$, the relative unevenness of the sample $R'_g = 0.653$, which indicates the imbalance of the sample and the presence of a minority class (q_3), and the number is $S^{21} \gg S^{23}$, $S^{22} \gg S^{23}$. Considering a sufficient number of instances for the third class, a decision was made to apply the method based on the removal of objects of the majority class (undersampling), which made it possible to obtain a uniform unique sample.

Various types of classifiers were trained using the available sample. As the studied classifiers, we shall use decision-making trees and groups of algorithms that implement discriminant analysis, Naive Bayes classifier, support vector machine (SVM), k-nearest neighbors, and artificial neural networks.

To provide training and test samples, the available sample was split into 80 % and 20 %, respectively.

To assess the quality of classifiers, the *Accuracy* classification quality metric was used [24, 27]:

$$Accuracy = \frac{TP + TN}{K}, \quad (13)$$

where *Accuracy* is the accuracy of the classification of the technical condition of UAV; *TP* is a true positive decision; *TN* – true-negative solution; *K* is the total number of instances.

The resulting dataset was tested by training different classification models in MATLAB with the default value of cross-validation and adjusting the algorithms' own parameters with the corresponding MATLAB functions. Fig. 2 shows examples of inconsistency matrices for the best results of one family of algorithms obtained in the training of different classification models.

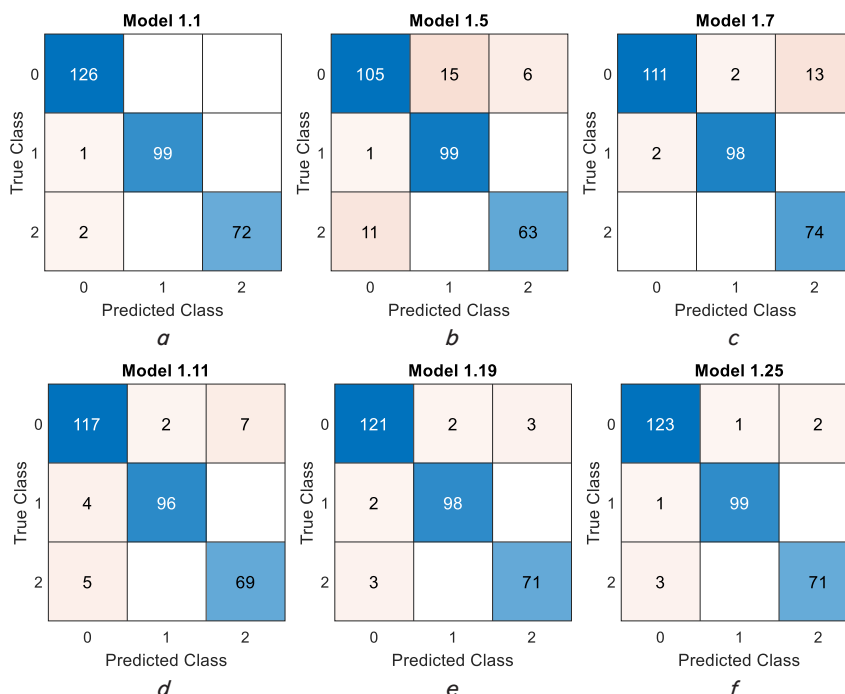


Fig. 2. Confusion matrices of the best models according to classification results: *a* – decision trees; *b* – quadratic discriminant; *c* – Naive Bayes (kernel); *d* – Support Vector Machine (fine Gaussian); *e* – method of k-nearest neighbors (weighted); *f* – neural networks (bilayered)

For clarity, the best and worst classification results for one family of algorithms for different numbers of instances in the training dataset are given in Table 1.

For this task, when training various classification models on a sample obtained by the proposed algorithm, the best results were demonstrated by the Decision Trees algorithm, even on the smallest sample size. The worst result was obtained by the Coarse KNN algorithm on the smallest training dataset, which significantly improved with an increase in the number of instances in the data set (from 40.7 % to 86.3 %).

Similar work on the formation of samples using the proposed method should be carried out for each specific UAV for which a technical condition recognition system is being designed. Persons who understand the principles of the system's functioning, the attributes of its construction, and the relationship between the parameters should be involved in such work.

Our results were compared with reported research results by other authors who solved the task of recognizing the technical condition of UAVs using artificial intelligence methods in terms of recognition accuracy (Table 2).

The results of the comparison of our results with the results by other authors' research indicate the achievement of better recognition accuracy. In particular, by 8.5 % for the model using discriminant analysis, 4.0 % for the model using decision trees, from 7.9 to 11.7 % for neural networks.

6. Discussion of results based on devising a method to form a sample for recognizing the technical condition of an unmanned aerial vehicle

In contrast to the recognition results given in [13, 28–30], the better result using the same machine learning algorithms can be explained by the higher quality of training data. Samples obtained using the developed method act as these data. Owing to stage 1. Analysis of the subject area, a subset of parameters relevant to the task being solved is selected from the entire set of parameters, formula (1). As a result of successive transformations, formulas (3) to (7), marking of data with the involvement of experts, which is reflected in formula (8), taking into account (9), a high-quality training dataset is obtained. It reflects the problems of the subject area, contains records without empty and anomalous values, has an even distribution of instances by classes.

An important feature is that the sample reflects the change in the technical condition of UAV that occurs during combat use and is also associated with intentional harmful effects carried out by the enemy.

In contrast to work [11], in which binary classification is carried out, as a result of our study, the possibility of classification of three UAV states was demonstrated. The study formalized the procedure for obtaining the training dataset, which fundamentally distinguishes our work from studies [9–14],

Table 1

Results of training classification algorithms for different numbers of instances of the training dataset

Type of training algorithm	Decision Trees	Discriminant Analysis		Naive Bayes		Support Vector Machine		k-nearest neighbor method		Neural networks	
		Quadratic discriminant	Linear discriminant	Kernel	Gaussian estimation	Fine Gaussian	Coarse Gaussian	Weighted	Coarse	Narrow	Bilayered
150 instances											
Accuracy, %	99.3	90.0	88.0	92.0	90.7	91.3	88.7	94.0	40.7	95.3	94.0
225 instances											
Accuracy, %	98.7	90.7	88.0	94.7	91.6	96.0	88.7	97.8	76.9	96.0	96.4
300 instances											
Accuracy, %	99.0	90.0	87.7	93.7	91.7	94.7	90.3	96.3	86.3	96.3	96.7

Table 2

Comparing the accuracy of recognition of the technical condition of UAVs using artificial intelligence methods

Type of training algorithm	Discriminant analysis (linear)		Decision Trees		Neural networks		
	Our result	Results in other studies	Our result	Results in other studies	Our result	Results in other studies	
Accura- cy, %	87.7	79.2% [13]	99.0	95.0 [28]	96.7	85.0 [29]	88.73 [30]
Diffe- rence, %	+8.5		+4.0			+11.7	+7.97

in which the procedure for processing the training dataset is not given enough attention or is not considered at all. The method obtained as a result of our research makes it possible to obtain a sample for recognizing different number of FSCs (depending on stage 1. Analysis of the subject area). This distinguishes it from the results reported in [9, 10, 13, 14], in which model training is aimed at recognizing a limited number of specific situations. In addition, according to the analysis of the subject area, the method allows taking into account the attributes of the combat use of UAVs and the deliberate influence of the enemy, which is not relevant for works [3–14].

Therefore, the proposed method makes it possible to fill in the insufficiently researched process of forming samples for recognizing the technical condition of UAVs, which is not given in previously analyzed scientific works [9–14].

The experiment showed that based on the sample formed using the proposed method, it is possible to construct effectively working models using various machine learning algorithms (Table 1). A comparison of the accuracy of recognition of the technical condition of UAVs using artificial intelligence methods with the results of other studies is given in Table 2.

The advantage of the proposed method is the possibility of its application to a wide range of unmanned aerial vehicles, low computational complexity, and the possibility of its implementation using programming languages or in the MATLAB environment.

A separate practical result, which partially implements the proposed method implementation algorithm, is a parser in the Python programming language, which allows automated extraction of data by the name of their attributes and fields from the UAV log file. Also, the practical result consists in determining the order of further processing of the received data, learning and setting the parameters of various classification models in MATLAB.

However, to apply the method, log files containing the flight parameters for each FSC to be recognized are required. And the organization of obtaining these log files for further processing is associated with certain difficulties. This can be considered a shortcoming of the proposed method.

One should also note certain restrictions on the use of the resulting datasets: the samples are formed on the basis of data on a specific UAV; accordingly, the obtained models can be used exclusively for UAV of this type. The specificity of UAV construction, differences in tactical and technical and flight characteristics make it necessary to form separate samples for the construction of models for recognizing FSCs of each UAV type.

Areas of further research are the analysis of FSCs characteristic of the combat use of Class I UAVs and the formation of a dataset for recognizing the appropriate set of states, the formalization of various flight stages. Further studies will also tackle recognition of FSCs that occur simultaneously, as well as automatic generation of rules by fuzzy inference systems.

7. Conclusions

1. A conceptual solution regarding the method for training dataset formation has been proposed, which builds on the CRISP-DM methodology. The solution differs from known

ones by constructing a uniformly distributed unique sample, taking into account the specificity of combat tasks under the conditions of enemy resistance. This has made it possible to increase the accuracy of recognition of Class I UAVs by the on-board system by an average of 8.0 %.

2. An experiment was conducted using decision trees, discriminant analysis, Naive Bayes classifier, support vector machine (SVM), k-nearest neighbors, artificial neural networks. The decision tree algorithm showed the highest accuracy of 99.3 % for this example. The sample built by the method implementation algorithm reflects the attributes of the technical structure of a specific UAV, meets the requirements of uniqueness, as well as the uniformity of distribution of instances by class.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

Funding

The study was conducted without financial support.

Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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