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Oleksii Chornyi,
Valerii Tytiuk,
Victor Busher,
Yurii Zachepa,
Volodymyr Grabko,
Andrii Romanets,
Yuliia Mala,
Dmytro Bilukhin,
Mykola Babyak,
Olena Huliesha

EXPERIMENTAL IDENTIFICATION OF UNMANNED AERIAL VEHICLE MODEL PARAMETERS BASED ON THE OPERATOR CONTROL SIGNAL AND THE OBJECT RESPONSE

The object of research is the process of identifying the parameters of the model of a separate channel of motion of an unmanned aerial vehicle (UAV). The paper addresses the problem of obtaining an accurate and simple computational procedure for estimating the time constant and damping coefficient of a UAV model represented as a second-order dynamic element, suitable for implementation in programmable controllers without the use of matrix libraries. The method is designed for implementation in programmable controllers without the use of matrix libraries. The identification procedure was developed using a dataset that includes 500 experimental UAV motion trials performed by operators in a computer-based simulator. The model parameters cover damping ratios in the range from 0.25 to 1.25 with a fixed time constant of 0.5 s. The obtained results provide an analytical calculation of the model parameters. Based on the theory of linear dynamic systems and the least squares method, the differential equation of the second-order system is transformed into a linear regression form. This is done using central finite differences to compute the first and second derivatives of the output signal. The parameter estimation is performed analytically, without using specialized software functions. This ensures compatibility with programmable logic controllers. To reduce sensitivity to noise during numerical differentiation, the experimental data are pre-smoothed. The analysis interval is limited to the dominant part of the transient response. The identified parameters show good agreement with the true model values. The relative error does not exceed 0.8% for the time constant and 1.2% for the damping ratio. The results can be used for PID controller autotuning and for the synthesis of adaptive control laws for UAVs. The identification procedure can be extended to online parameter estimation during flight, as well as to higher-order and nonlinear dynamic models.

Keywords: *identification, second-order dynamic model, UAV, model parameters, programmable controller.*

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1. Introduction

Unmanned aerial vehicles today occupy an important place in surveillance, monitoring, delivery, search and rescue operations and military applications. Their mass implementation is associated not only with the development of the element base, sensors and computing resources, but also with increasing requirements for the accuracy, reliability and predictability of automatic control systems. To ensure stable and safe flight, it is necessary to develop mathematical models that adequately reflect the UAV dynamics and can be used as a controller synthesis. In modern scientific works on the identification of UAV dynamics, methods of system identification based on experimental data from flight tests are widely used [1–3]. For quadcopters and fixed-wing UAVs, different approaches to model identification are used. A number of methods work in the time domain, others in the frequency domain; others use the maximum likelihood method, the recursive least squares method, and optimization procedures in which the model parameters are selected so that its response is as close as possible to the real behavior of the device [1, 4].

For example, two-stage identification schemes are used for inexpensive UAVs. First, the flight trajectory is restored, and then the model parameters are refined using temporal MLE identification. This approach makes it possible to work even with data from inexpensive IMU sensors, even in hover mode [1]. For fixed-wing UAVs, methods for identifying longitudinal motion are also being developed. In this case, the model parameters are determined from limited or not fully controlled flight data, reducing the difference between experimental trajectories and trajectories obtained from the model [5, 6].

Methods for identifying parameters based on metaheuristic algorithms are being actively developed. These include, in particular, the particle swarm algorithm, genetic algorithms and other optimization methods [7, 8]. They allow estimating the moments of inertia, aerodynamic coefficients and other UAV parameters based on the results of experimental maneuvers. Such methods can also be applied to closed-loop control systems when the device is already operating under the action of the controller [7, 3].

The advantage of these approaches is the high accuracy of the obtained models. At the same time, they usually require significant computing resources, high-quality measuring equipment and more complex software implementation. Because of this, they cannot always be directly used in simple programmable controllers or training and training complexes with limited resources [7, 8].

A separate direction is research in which the UAV parameters are determined taking into account the operator's control [9]. They analyze not only the dynamics of the device, but also the dynamic characteristics of the pilot-operator, stochastic disturbances, measurement noise and communication channel limitations. This is especially true for remote control systems, where the operator interacts with the object through the simulator interface, and the quality of training directly depends on the adequacy of the mathematical model of individual motion channels [9].

Practice shows that in many applied UAV control problems it is advisable to isolate individual dynamics channels – pitch, roll, height movement, linear or longitudinal movement – and represent them in the form of low-order models, in particular normalized second-order dynamic links [2, 4, 5]. This provides a simple physical interpretation of parameters such as time constant, damping coefficient and gain coefficient, and allows the use of standard methods of controller analysis and synthesis [2, 3]. In real conditions, these parameters change due to variations in mass-inertial characteristics, placement and discharge of the payload, differences between individual instances of the devices, as well as due to the action of external disturbances [2, 7].

Increased requirements for identification algorithms for training and testing complexes are defined in [7, 8]. They require significant computational resources to ensure the accuracy of calculations. In computer simulators with UAV control by an operator, algorithms are used with registration of input and output signals when working out test tasks, for example, reaction to a step impact [9].

Modern research on the identification of UAV model parameters is directed in different directions. Some works are aimed at building models of individual control channels, for example, pitch, roll or movement in height. Other researches describe the UAV movement more fully, taking into account aerodynamics, structural flexibility and interaction between the operator and the device.

For practical tasks, a very complex model is not always needed. It is often more important to have a simple but sufficiently accurate dynamic model that can be obtained from experimental data. Such a model is convenient to use for analyzing UAV behavior, adjusting regulators and testing automatic control systems.

Most of the works consider the identification of parameters in the time domain based on the use of special test signals. In [1], a two-stage method for identifying the parameters of a low-cost quadcopter was proposed, which combines a preliminary assessment based on simplified models and subsequent refinement optimization based on flight data. In [10], a detailed identification of heterogeneous multirotor UAVs was performed, considering different configurations and using frequency and time characteristics to build linear models of individual control channels. The possibilities of using the extended Kalman filter (EKF) for simultaneous assessment of the states and parameters of multirotor models, which allows for real-time identification, are shown in [11].

A separate group of works is devoted to fixed-wing UAVs. The research of a system for identifying the longitudinal motion of a small unmanned aerial vehicle based on limited flight data obtained in conditions of unplanned maneuvers is shown in [12]. It is also shown that even with limited and noisy measurements, adequate second-order models for pitch and velocity channels can be obtained using combined frequency and time criteria for identification quality. In [13], several metaheuristic algorithms were used to identify a small UAV. Their application is aimed at reducing the difference between experimental flight trajectories and trajectories obtained from the model. The research results show that the L-SHADE algorithm provides better results compared to classical approaches. Such algorithms take into account both time indicators, in particular, overshoot and transient time, and frequency characteristics, which provides a comprehensive assessment of the quality of the model.

In a number of researches, the main attention is paid to optimization methods used for more accurate tuning of model and controller parameters. For example, in [14], a method for determining quadcopter parameters based on the PSO particle swarm algorithm was proposed. Its use provides a significant reduction in the error between the measured and calculated motion trajectories.

A separate direction is the application of machine learning methods and neural networks. In [15], an approach to identifying linear processes, in particular UAV models, based on real-time learning is proposed. Neural network models are used to approximate the dynamics of an object and estimate its parameters with minimal operator involvement. Such methods provide high accuracy, but are not convenient for tuning regulators, because they require large amounts of data for training and significant computing resources. Therefore, they are not always convenient for typical engineering tasks.

In [16], the dynamics of the UAV pilot-operator in stochastic conditions were identified, focusing on the construction of a mathematical model "man-operator-device" taking into account noise and random influences. The practical significance of the work lies in the possibility of using the obtained models to improve the efficiency of UAV control systems, create simulators, and also to assess the reliability and quality of operators' work in difficult conditions. The work [17] is devoted to the development of a mathematical model of quadcopter control, with a detailed description of the dynamics of DC motors and the corresponding transfer functions, which can be used as basic objects for constructing simplified models of individual control channels. In [18], a model of UAV motion was constructed based on the algebra of dual quaternions, which allows describing the spatial kinematics of the aircraft taking into account both translational and rotational motion in a single mathematical apparatus [19]. In [20], an acoustic method for identifying the use of UAVs as sources of emergency situations is proposed, where identification concerns not so much the dynamics parameters as the recognition of types of devices by their acoustic signals using cluster analysis and wavelet transforms.

In addition to the above research areas, a fairly influential area in the development of methods for identifying and analyzing dynamic systems is the article devoted to modeling automatic control systems. In particular, in [21], a laboratory stand is proposed for analyzing automatic control systems using a fuzzy controller. The laboratory complex created by the authors allows to study the dynamic properties of objects, analyze the quality of regulation, and perform experimental verification of control algorithms. Such complexes are important tools for studying the dynamic properties of technical systems, as well as for verifying algorithms for identifying model parameters based on real experimental data.

In [22], an approach to quasi-optimal control of a DC motor is proposed, which is based on the use of analytical methods for synthesizing regulators and analyzing the dynamic characteristics of the system. The results obtained by the authors indicate an increase in the accuracy and speed of control systems, which is of direct importance for the creation of effective electric drives and actuator systems of UAVs.

In work [23], the dynamic characteristics of a quasi-resonant converter with zero-current switching were investigated. The authors analyzed the influence of the parameters of the resonant circuit and the load on the dynamic behavior of the ACS. Such researches are important for understanding the processes occurring in the energy subsystems of controlled objects, including UAVs.

The issue of increasing the reliability of modeling of electromechanical systems was considered in work [24], where the authors proposed methods for improving the modeling of electric motors when solving technical and economic problems. The authors proved that the use of more accurate models of electric motors allows to increase the adequacy of computer modeling of complex technical systems and improve the results of optimizing their operating modes.

An important tool for studying dynamic systems is also the analysis of phase trajectories. In [25], a research of phase trajectories of third-order dynamic objects was conducted. The proposed approach allows analyzing the stability and nature of transient processes in complex dynamic systems, which can be used in the research of UAV motion and control models.

A literature review of the above-mentioned scientific works indicates the active development of methods for modeling, identification, and optimal control of dynamic systems. At the same time, for practical tasks of controlling unmanned aerial vehicles, relatively simple parametric models are important, which can be identified from experimental data and used to configure controllers and create training and test complexes.

An analysis of modern literature sources indicates the active development of research related to the identification of UAV dynamic properties. The main attention in these researches is paid to the construction of models oriented to control tasks. Such models should accurately reflect the physical properties of the object. At the same time, they should be convenient for synthesizing controllers and checking results in the MATLAB/Simulink environment. A separate requirement is the possibility of implementing such models in embedded computing systems.

In [26], the problem of identifying a quadcopter model and synthesizing an $H_{¥}$-controller for the orientation channel was considered, which confirms the feasibility of building such models that are suitable not only for describing the dynamics of the object, but also for the further synthesis of control systems. In [27], an approach to reconfiguring multirotor UAV control based on online identification using the sparse regression method was proposed, which shows the relevance of models that can be updated during operation and take into account changes in object parameters in real time. In [28], the identification of the quadcopter orientation model is performed using the subspace identification method, and the results obtained are focused on building engineering-suitable models for analyzing dynamics and further use in automatic control systems. In [29], closed-loop identification of UAVs under conditions of two-frequency discretization was investigated, which demonstrates the possibility of obtaining adequate dynamic models even in modes close to the real operation of the control system, when experimental data are formed in a closed loop. In the review [30], closed-loop subspace identification methods are systematized, which is an important theoretical basis for building models of dynamic objects based on experimental data in feedback conditions, which are also typical for UAV control tasks. Modern research, for example [31], increasingly proceeds from an engineering compromise: for practical control, it is advisable to describe individual channels by simplified parametric dependencies of low order, which preserve the main dynamic properties of the object, but do not overload the procedure for setting up controllers. This logic is clearly traced in [31], where the identification of quadcopter dynamics is considered as a problem of obtaining models from experimental data in a closed loop, namely, the suitability of the models for further control. A characteristic trend of modern scientific research is that the identification is performed not in ideal (laboratory) conditions, but on the basis of limited or partially uncontrolled data with the presence of additional noise. In this case, the work [1] devoted to the identification of the dynamic properties of UAVs, in which the longitudinal motion parameters are estimated from limited experimental data obtained during unplanned flight modes, is of interest. The results obtained [1] demonstrate the possibility of constructing adequate parametric models in the absence of specially organized identification experiments. Also, approaches to the identification of low-cost multirotor platforms are being developed in parallel, where the parameter estimation procedure is specially adapted to the use of noisy measurements from inertial sensors (IMU) and limited possibilities of experimental excitation of the system itself [12]. Such researches confirm that even under conditions of low quality of measurement information, it is possible to obtain engineering-suitable models of the dynamic properties of UAVs, which is especially valuable for practical control tasks and the creation of training and simulator complexes.

A separate direction is formed by works in which the parameters of UAV models are estimated in real time. In particular, in [11] an approach based on the extended Kalman filter is proposed, which allows estimating the parameters of a multirotor aircraft in a single identification process using measurements from onboard sensors, without the use of specialized bench experiments. In this case, the model parameters are included in the state vector and are estimated together with dynamic variables, which ensures their consistent refinement in the process of work. Similar approaches are the basis of methods for adaptive identification and control of UAVs [32], where parameters reflecting the inertial and aerodynamic properties of the aircraft are considered as variable values [33]. This confirms that the variation of parameters of dynamic UAV models is an integral property of the system, which must be taken into account when building models and identification algorithms. In [34] it is proven that the connection of Matlab/Simulink with a virtual flight environment is an effective tool not only for checking controllers, but also for analyzing identified models according to data from virtual or semi-real experiments. It is also emphasized that even when the task formally concerns energy consumption, in practice the researcher comes to the need to allocate separate channels, parameterize driving and inertial effects and further experimental validation. For training and simulation systems, this means that the Simulink-compatible identification procedure has not an auxiliary, but a central status, because it is it that closes the circle of "experiment – parameter estimation – model correction – re-verification".

Despite the significant number of works devoted to the system identification of UAVs, the following issues remain insufficiently resolved in the cited sources:

- justification of the application of the second-order model to individual UAV motion channels;
- construction of an analytical procedure for estimating model parameters based on experimental input-output data obtained on a computer simulator with the participation of the operator;
- ensuring the stability of this procedure to noise, as well as its adaptation to implementation in programmable controllers without the use of specialized matrix libraries. This article is devoted to solving these issues.

Thus, *the object of research* is the process of identifying the parameters of the model of an individual UAV motion channel.

The aim of research is to develop an analytical procedure for identifying the parameters of the model of an individual UAV motion channel based on the operator’s control signal and the reaction of the UAV model, with an orientation towards the implementation of the algorithm in programmable controllers. This will make it possible to apply the obtained parameters in the auto-tuning of regulators and the construction of adaptive UAV control systems.

To achieve the aim, it is necessary to perform the following objectives:

1) to substantiate the structure of the model and parameters of the UAV motion channel in the form of a second-order dynamic link;

2) to develop an algorithm for identifying the parameters of the UAV model based on the operator control signal registered on the computer simulator and the response of the UAV model to determine the time constant and damping coefficient of the second-order dynamic link;

3) to develop an algorithm for identifying the parameters of the UAV model based on experimental data for programmable controllers.

2. Materials and Methods

The following scientific methods were used in the research of the process of identifying the parameters of a dynamic model of unmanned aerial vehicle (UAV), represented as a normalized second-order link:

The following scientific methods were used in the research:

- analysis method – when studying the structure of UAV dynamic models and substantiating the feasibility of representing individual motion channels as second-order links;
- mathematical modeling method – when forming a dynamic model of an object in the form of a second-order differential equation and the corresponding transfer function;
- system identification method – when determining model parameters from experimental input-output data;
- experimental data processing methods – when preparing signals for identification, in particular for numerical differentiation, noise smoothing and selecting an informative section of the transient process;
- algorithmic optimization methods – when adapting the identification procedure to implementation in programmable controllers with limited computing resources.

The analysis method was used to substantiate the model structure, according to which the dynamics of the pitch, altitude and translational motion channels of the UAV can be described by a normalized second-order link. This approach provides accuracy of description and simplicity of further use of the model in control system synthesis problems.

The mathematical modeling method was used to describe the dynamics of the object in the form of a differential equation, the parameters of which are the time constant and the damping coefficient, which have a clear physical interpretation.

The system identification method was implemented by determining the model parameters based on experimental data of the "input-output" type. Identification is reduced to the selection of such model parameters that minimize the deviations between the experimental and model signals.

Experimental data processing methods were used to ensure the stability of the identification procedure to noise and the discreteness of the signals, in particular:

- numerical differentiation of the first and second derivatives of the output signal was performed using central finite differences;
- to reduce the noise effect, smoothing of signals using the moving average method was applied;
- the analysis interval was limited to the section of the main transient process, which allows excluding uninformative sections, which include the initial delay and the steady state.

Algorithmic optimization methods were used to adapt the identification procedure to implementation in programmable controllers. At the same time, matrix operations were replaced by the calculation of scalar sums and the solution of a system of linear algebraic equations. This made it possible to avoid the use of specialized matrix libraries and ensure the compatibility of the algorithm with limited computing resources.

Experimental verification of the proposed identification procedure was performed using a computer simulator for controlling a model of a separate channel of motion of an unmanned aerial vehicle. The simulator was implemented in the MATLAB/Simulink environment, which provided the possibility of forming a dynamic model of the object, registering "input-output" signals, visualizing the control process and further processing of experimental data.

The Logitech Extreme 3D Pro L942-000031 joystick was used as the operator's control signal input device. Using the joystick, the operator formed the control action u(t), trying to ensure tracking of the given signal, which was generated in the form of a step effect. The amplitude and moment of appearance of the step signal were formed randomly, which made it possible to obtain a set of experimental implementations with different initial conditions and the nature of the operator's reaction.

The simulator does not implement the full spatial motion of a specific physical sample of the UAV, but a separate channel of its motion, represented in the form of a normalized second-order dynamic link.

3. Results and Discussion

3.1. Justification of the model structure and parameters of the UAV motion channel in the form of a second-order dynamic link

3.1.1. Justification of the model structure and pitch channel parameters

Most modern UAV control methods are based on the established practice of modeling pitch, altitude, and linear motion channels as second-order coupled models with effective mass-inertial and damping parameters [2, 6]

$$W(s)=\frac{k}{T^2s^2+2Tk_{cs}s+1},$$

where T – the generalized time constant; k_{cs} – the normalized damping coefficient; k – the static gain of the object.

This form can be obtained from a physically based model of the "mass-damper-spring" type

$$M\ddot{x}+C\dot{x}+K_sx=K_uu,$$

after normalization

$$W(s)=\frac{X(s)}{U(s)}=\frac{K_u}{Ms^2+C_s+K_s}=\frac{K_u/K_s}{\left(\frac{M}{K_s}\right)s^2+\left(\frac{C}{K_s}\right)s+1}.$$

Comparing the denominator with the normalized form, it is possible to obtain the analytical relations:

$$T^2=\frac{M}{K_s},\ 2Tk_{cs}=\frac{C}{K_s},\ k=\frac{K_u}{K_s}.$$

From here:

$$T=\sqrt{\frac{M}{K_s}},\ k_{cs}=\frac{C}{2TK_s}=\frac{C}{2\sqrt{MK_s}},\ k=\frac{K_u}{K_s}. \tag{1}$$

For a UAV, a suspended load of mass mx is located on a suspension under the body of the device. This changes both the total mass of the device in the translational motion channels and the moment of inertia in the angular channels. Let's consider three main control channels: pitch, height movement and linear translational motion.

For the pitch channel of the UAV, the dynamics of small deviations of the angle θ around the transverse axis of rotation can be written as

$$J\ddot{\theta}+C_\theta\dot{\theta}+K_a\theta=K_{u,\theta}u_\theta, \tag{2}$$

where J – the moment of inertia of the aircraft relative to the pitch axis; C_θ – the coefficient of aerodynamic damping in angular velocity; K_a – the "stiffness" in angle (the aerodynamic moment that returns the aircraft to the equilibrium state); $K_{u,\theta}$ – the coefficient of conversion of the control signal (for example, the thrust differential or the deflection of the controls) into a moment; u_θ – the corresponding control signal.

Transfer function from u_θ to θ

$$W_\theta(s)=\frac{\Theta(s)}{U_\theta(s)}=\frac{Ku,\theta}{Js^2+C_\theta s+K_a}. \tag{3}$$

Let's reduce it to a normalized form (by analogy with (1))

$$W_\theta(s)=\frac{k_\theta}{T_\theta^2 s^2+2T_\theta k_{cs,\theta}s+1},$$

where:

$$T_\theta=\sqrt{\frac{J}{K_a}},\ k_{cs,\theta}=\frac{C_\theta}{2\sqrt{JK_a}},\ k_\theta=\frac{K_{u,\theta}}{K_a}. \tag{4}$$

A suspended load of mass m_L, located at a distance h from the axis of rotation (under the body on the suspension), changes the moment of inertia of the UAV according to the Huygens-Steiner theorem:

- before dropping the load

$$J_1=J_u+m_L h^2;$$

- after dropping

$$J_2=J_u,$$

where J_u – the moment of inertia of the "clean" aircraft without load. It is obvious that $J_2 < J_1$.

Substituting into (4), let's obtain:

$$T_{\theta 1}=\sqrt{\frac{J_1}{K_a}},\ T_{\theta 2}=\sqrt{\frac{J_2}{K_a}},\ T_{\theta 2}<T_{\theta 1},$$

$$k_{cs,\theta 1}=\frac{C_\theta}{2\sqrt{J_1K_a}},\ k_{cs,\theta 2}=\frac{C_\theta}{2\sqrt{J_2K_a}},\ k_{cs,\theta 2}>k_{cs,\theta 1}.$$

The static coefficient

$$k_\theta=\frac{Ku,\theta}{K_a},$$

in the first approximation practically does not change, since the geometry of the body and controls does not change when the load is dropped.

Thus, dropping the suspended load reduces the moment of inertia J, which leads to a decrease in the time constant T_θ and accelerates the reaction of the object, and increases the normalized damping coefficient $k_{cs,\theta}$. The coefficient k_θ can be considered practically constant.

3.1.2. Justification of the model structure and parameters of the height movement channel

For the vertical channel (movement in height h) let's use the linearized model

$$M\ddot{h}+C_h\dot{h}+K_{s,h}h=K_{u,h}u_T, \tag{5}$$

where M – the mass of the UAV with the load (effective mass in vertical movement); C_h – the aerodynamic damping in vertical speed; $K_{s,h}$ – the coefficient of "vertical stiffness" of the aerodynamic characteristic; $K_{u,h}$ – the coefficient of conversion of the thrust control signal into vertical force; u_T – the thrust command signal.

Similarly (1) let's obtain the analytical expressions:

$$W_h(s)=\frac{H(s)}{U_T(s)}=\frac{k_h}{T_h^2s^2+2T_hk_{cs,h}s+1},$$

$$T_h=\sqrt{\frac{M}{Ks,h}},\ k_{cs,h}=\frac{C_h}{2\sqrt{MK_{s,h}}},\ k_h=\frac{K_{u,h}}{K_{s,h}}. \tag{6}$$

If the mass of the device with the suspended load has the expression

$$M_1=m_u+m_L,$$

then after dropping the load:

$$M_2=m_u,\ M_2<M_1,$$

let's assume that the load is compact and located close to the center of mass. Then let's assume that C_h, $K_{s,h}$ practically do not change and:

$$T_{h1}=\sqrt{\frac{M_1}{Ks,h}},\ T_{h2}=\sqrt{\frac{M_2}{K_{s,h}}},\ T_{h2}<T_{h1},$$

$$k_{cs,h1}=\frac{C_h}{2\sqrt{M_1K_{s,h}}},\ k_{cs,h2}=\frac{C_h}{2\sqrt{M_2K_{s,h}}},\ k_{cs,h2}>k_{cs,h1}.$$

In this case, the coefficient

$$k_h=\frac{K_{u,h}}{K_{s,h}},$$

depends on which variable is chosen as the output:

- if the output is the height h, and the coefficients $K_{u,h}$ and $K_{s,h}$ are linearization coefficients around the hovering mode, then the change in mass will have little effect on their ratio, and it is possible to consider k_h practically constant;
- if the output is vertical acceleration or speed, then with a smaller mass the thrust increases and k_h will increase with decreasing M.

This means that dropping the load reduces the mass M, which clearly leads to a decrease in the time constant T_h and an increase in damping $k_{cs,h}$.

3.1.3. Justification of the model structure and parameters of the linear translational motion channel

Let's consider the UAV movement in the longitudinal direction, for example, along the axis (horizontal speed or position)

$$M\ddot{x}+C_x\dot{x}+K_{s,x}x=K_{u,x}u_x, \tag{7}$$

where M – the total mass of the UAV with the load (the same as in the vertical channel); C_x – the aerodynamic damping along the translational motion; $K_{s,x}$ – the effective "stiffness" in this channel (can describe stabilizing aerodynamic forces, binding to a certain cruising speed, etc.); $K_{u,x}$ – the control conversion coefficient (pitch, thrust change, rudder deflection) into force along the x-axis; u_x – the corresponding control signal.

The reduction to the normalized model gives:

$$W_x(s)=\frac{X(s)}{U_x(s)}=\frac{k_x}{T_x^2s^2+2T_xk_{cs,x}s+1},$$

$$T_x=\sqrt{\frac{M}{K_{s,x}}},\ k_{cs,x}=\frac{C_x}{2\sqrt{MK_{s,x}}},\ k_x=\frac{K_{u,x}}{K_{s,x}}. \tag{8}$$

As in the previous case, when the suspended load is dropped, the mass changes from $M_1 = m_u + m_L$ to $M_2 = m_u$, the relations (8) give

$$T_{x2} < T_{x1},\ k_{cs,x2} > k_{cs,x1}.$$

A feature of the linear channel is that it is the "control signal → acceleration/velocity" that is important for it, and not the static position.

Thus, with a smaller mass, the same aerodynamic or traction forces create a larger acceleration, i. e. the effective coefficient $K_{u,x}$ relative to the normalized output increases, which means that it can be stated that k_x increases when the load is dropped.

To summarize, for the three considered channels – pitch, height movement and linear translational movement – dropping a suspended load under the UAV body has a systemic effect:

- in all channels the "inertial" parameter (mass or moment of inertia) decreases, which leads to a decrease in the time constant T and, accordingly, to a "faster" reaction of the object;
- the normalized damping coefficient k_{cs} increases, since the same damping effect acts on a smaller mass/inertia;
- the change in the static coefficient k is most noticeable in channels where the output is linear motion (velocity, acceleration), since the control efficiency is inversely proportional to the mass; in angular channels, the pitch at the exit at an angle can be considered practically constant.

This proves the need to take into account changes in T, k_{cs} and k in the UAV model when synthesizing and adapting the control system regulators in suspended load dropping modes.

3.2. Development of an algorithm for identifying UAV model parameters based on the operator control signal registered on the computer simulator and the UAV model response to determine the time constant and damping coefficient of the second-order dynamic link

The theoretical analysis conducted shows that the model parameters respond sensitively to changes in mass-inertial characteristics, in particular when dropping a suspended load. This confirms the need for prompt updating of model parameters in real operating conditions to ensure stability and control quality.

However, for the practical implementation of adaptive control algorithms, it is not enough to know the model structure – it is necessary to have a reliable mechanism for its identification using real data. It is especially important that the identification procedure is simple, does not require complex computational libraries and can be implemented even in programmable controller environments.

Let's formulate the goal of identification as determining the parameters of the second-order dynamic link using experimental data $u(t)$ and $y(t)$. Let's assume that the object is described by a second-order transfer function of the form [14]

$$W(s)=\frac{k}{T^2s^2+2Tk_{cs}+1}. \tag{9}$$

It is necessary to estimate the parameters T and k_{cs} from the experimental data.

The transfer function (9) corresponds to the differential equation

$$T^2\frac{d^2y(t)}{dt^2}+2Tk_{cs}\frac{dy(t)}{dt}+y(t)=u(t). \tag{10}$$

Let's transfer $y(t)$ to the right-hand side

$$T^2\frac{d^2y(t)}{dt^2}+2Tk_{cs}\frac{dy(t)}{dt}=u(t)-y(t). \tag{11}$$

Let's introduce new parameters

$$p_1 = T^2, p_2 = 2Tk_{cs}, \tag{12}$$

then the equation takes on a linear form in the parameters

$$p_1\frac{d^2y(t)}{dt^2}+p_2\frac{dy(t)}{dt}=u(t)-y(t). \tag{13}$$

Thus, the identification is reduced to estimating p_1, p_2 and, using (12), calculating T and k_{cs}.

Let's have a sample of N samples:

$$t_k, y_k, u_k, k = 0, 1, ..., N-1,$$

with a uniform step Δt.

To reduce the influence of noise and uninformative sections, for parameter estimation it is possible to choose a time interval covering the main part of the transient process.

Let's denote the set of indices used in the calculations by $K\subset\{1,...,N-2\}$ (the extreme points are not used because of the calculation of central differences).

For each point $k \in K$, the first and second derivatives of the output signal are approximately calculated using the central difference formulas:

- first derivative

$$\dot{y}_k\approx\frac{y_{k+1}-y_{k-1}}{2\Delta t}; \tag{14}$$

- second derivative

$$\ddot{y}_k\approx\frac{y_{k+1}-2y_k+y_{k-1}}{\Delta t^2}. \tag{15}$$

Let's use the obtained sequences $\dot{y}_k$ and $\ddot{y}_k$ in model (13).
Substituting (14), (15) into (13) for each $k \in K$, let's obtain

$$p_1\ddot{y}+p_2\dot{y}=u(t)-y(t). \tag{16}$$

For the entire set of equations (16), let's write this in matrix form

$$Xp\approx z, \tag{17}$$

where:

$$X=\begin{bmatrix}\ddot{y}_{k1} & \dot{y}_{k1}\\ \ddot{y}_{k2} & \dot{y}_{k2}\\ \vdots & \vdots\\ \ddot{y}_{kM} & \dot{y}_{kM}\end{bmatrix},\ p=\begin{bmatrix}p_1\\ p_2\end{bmatrix},\ z=\begin{bmatrix}u_{k1}-y_{k1}\\ u_{k2}-y_{k2}\\ \vdots\\ u_{kM}-y_{kM}\end{bmatrix},$$

and $M=|K|$ – the number of samples used.

The parameter vector p is determined from the condition of the minimum of the quadratic error function

$$J(p)=\sum_{k\in K}\left(z_k-p_1\ddot{y}_k-p_2\dot{y}_k\right). \tag{18}$$

The solution of the least squares problem for (17) has the form

$$\widehat{p}=(X^TX)^{-1}X^Tz, \tag{19}$$

where $\widehat{p}=\begin{bmatrix}\widehat{p}_1 & \widehat{p}_2\end{bmatrix}$ – the parameter estimates.

Now the required model coefficients are calculated as:

$$\widehat{T}=\sqrt{\widehat{p}_1},\ \widehat{k}_{cs}=\frac{\widehat{p}_2}{2\widehat{T}}. \tag{20}$$

To control the quality of identification, equation (10) is solved using the found parameters $\widehat{T}$, $\widehat{k}_{cs}$ and the real input signal $u(t)$. In discrete form, equation (10) can be integrated numerically (for example, by the Euler method or more accurate methods), which allows to obtain the model response $y_{mod}(t_k)$.

Comparing the experimental output y_k and the model output $y_{mod,k}$, let's calculate the quality criteria (mean square error, maximum deviation, graphical comparison, etc.). Good agreement confirms the correctness of the selected model structure and the parameter estimation procedure.

The identification of parameters according to the presented method involves the use of Matlab installed on the PC. In the calculation process, it becomes necessary to calculate matrices and find parameters according to (19), as a solution to the matrix equation.

3.3. Development of an algorithm for identifying UAV model parameters using experimental data for programmable controllers

To use the developed method in programmable controllers, it is necessary to avoid special functions and replace them with simple algebraic operations.

If the OLS model has the form:

$$p_1\ddot{y}_k + p_2\dot{y}_k \approx z_k,\ z_k = u_k - y_k,$$

then instead of matrices, 5 sums need to be calculated.

Let's introduce the substitution:

$$a_k = \ddot{y}_k;\ b_k = \dot{y}_k;\ z_k = u_k - y_k.$$

Then let's calculate:

$$S_{aa} = \Sigma a_k^2;\ S_{bb} = \Sigma b_k^2;\ S_{ab} = \Sigma a_k b_k;$$

$$S_{az} = \Sigma a_k z_k;\ S_{bz} = \Sigma b_k z_k.$$

Now p_1 and p_2 are determined by solving the system of linear algebraic equations:

$$S_{aa}p_1 + S_{ab}p_2 = S_{az},$$

$$S_{ab}p_1 + S_{bb}p_2 = S_{bz}.$$

An analytical solution can be obtained, for example, by Cramer's method:

$$\Delta = S_{aa}S_{bb} - S_{ab}^2,$$

$$p_1 = \frac{S_{az}S_{bb} - S_{bz}S_{ab}}{\Delta},$$

$$p_2 = \frac{S_{bz}S_{aa} - S_{az}S_{ab}}{\Delta}.$$

Then

$$p_1 = T^2,\ p_2 = 2Tk_{cs},$$

$$T = \sqrt{p_1},\ k_{cs} = \frac{p_2}{2T}.$$

It should be borne in mind that numerical differentiation is sensitive to noise. Therefore, before calculating the derivatives, it is necessary to smooth out y_k a little, for example, by the simple moving average method, or take a larger step for the derivative (for example, after 2–3 samples).

Experimental verification was carried out on the basis of data obtained on a simulator with the participation of operators. The experiment was attended by 20 respondents who, working on the Matlab/Simulink simulator model developed by the authors (Fig. 1), used a joystick to track the generated signal in the form of a step. Moreover, the step parameters: amplitude and time were formed randomly.

In the research process, a Logitech Extreme 3D Pro L942-000031 joystick was used, Fig. 2.

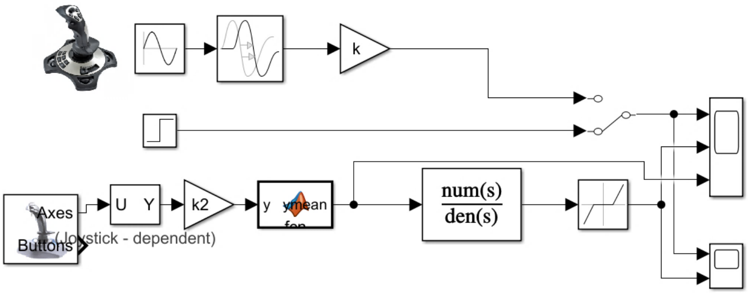
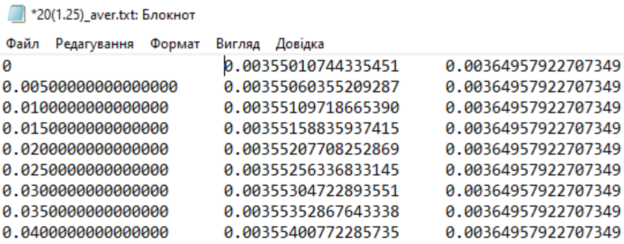


Fig. 1. Computer simulator

Fig. 2. Appearance of the Logitech Extreme 3D Pro L942-000031 joystick used in the experimental research

The operator's actions were recorded in a text file containing three columns (Fig. 3).

Where the first column of the file is time, the second column is the output signal y_k, the third column is the input signal u_k, the sampling step Δt is constant (in the experiment Δt = 0.005 s).



```
0                      0.00355010744335451      0.00364957922707349
0.00500000000000000    0.00355060355209287      0.00364957922707349
0.0100000000000000     0.00355109718665390      0.00364957922707349
0.0150000000000000     0.00355158835937415      0.00364957922707349
0.0200000000000000     0.00355207708252869      0.00364957922707349
0.0250000000000000     0.00355256336833145      0.00364957922707349
0.0300000000000000     0.00355304722893551      0.00364957922707349
0.0350000000000000     0.00355352867643338      0.00364957922707349
0.0400000000000000     0.00355400772285735      0.00364957922707349
```

Fig. 3. Fragment of experimental data recording

The object model in the form of a transfer function of a second-order dynamic link

$$W(s) = \frac{k}{T^2s^2 + 2Tk_{cs} + 1}$$

was given in the block num(s)/den(s) (Fig. 1).

During the experiments, the parameters of the object model were changed (Table 1).

Each of the respondents performed object control for five different values of k_{cs}: 0.25, 0.5, 0.75, 1.0, 1.25 s for 5 attempts. The total number was 500 attempts for each k_{cs} value.Using the method considered in [1], equivalent operator characteristics were obtained when controlling a dynamic object. The results of experimental researches are shown in Fig. 4.

Let's carry out numerical identification of experimental data according to the presented method. To reduce the influence of noise and "dead" sections, it is not possible to take in calculations the initial fragment of data, where there is no reaction yet, as well as the section with a steady process, where derivatives ≈ 0.

Table 1

Transfer function parameters adopted in experimental researches

Parameters of the object transfer function	
Time constant T	Damping coefficient k_{cs}
0.5	0.25
	0.5
	0.75
	1.0
	1.25

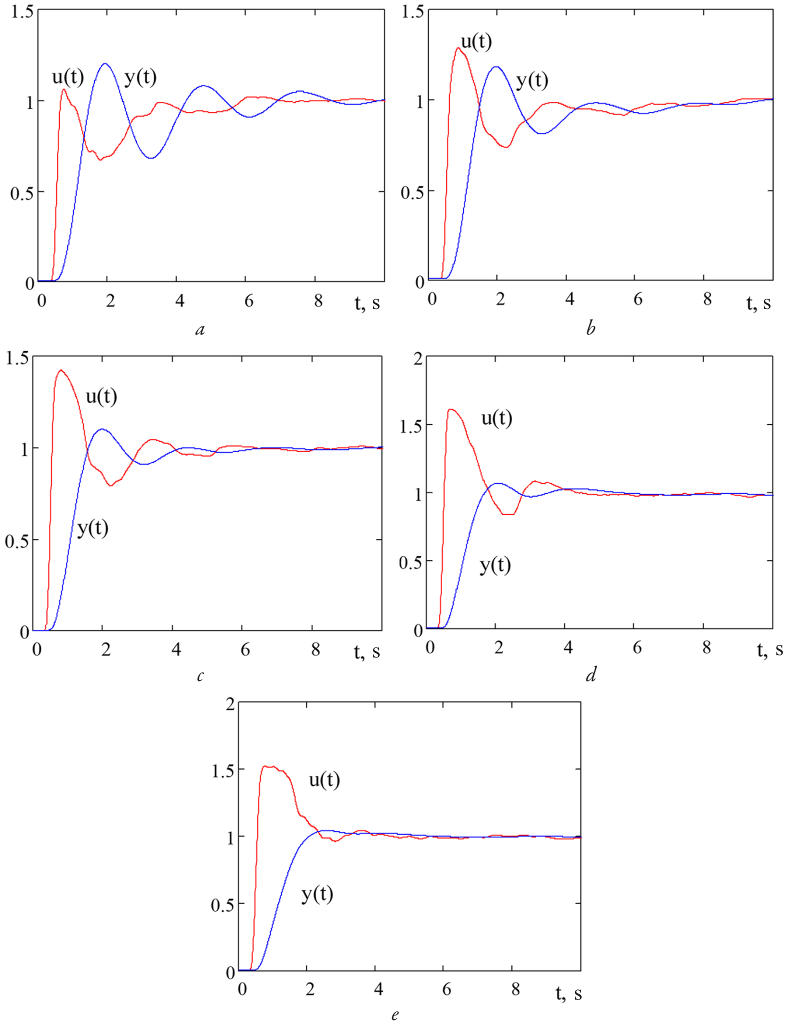


Fig. 4. Time characteristics of operator control of an object of the form (9) at the step reaction: *a* – k_{cs} = 0.25, *b* – k_{cs} = 0.5, *c* – k_{cs} = 0.75, *d* – k_{cs} = 1.0, *e* – k_{cs} = 1.25. Red line – operator reaction, blue line – object output

For example, in the obtained experimental data it is convenient to take an interval of approximately $t \in [0.5 \text{ s}; 5 \text{ s}]t$, in the section of the main transient process.

Let's carry out calculations in Matlab according to the scenario for programmable controllers. The results of calculations are summarized in Table 2.

The developed procedure for identifying object parameters can be implemented on the basis of microcontrollers used in industrial devices.

The main operations that the controller needs to perform are data accumulation and calculation of parameters T, ξ. Therefore, to verify the feasibility of implementing the proposed system, a program was developed for Arduino series controllers: Mega2560 and Intel Galileo Gen. 2 (Fig. 5).

Table 2

Identification results

Given		Identified	
Time constant	Damping coefficient	Time constant	Damping coefficient
0.5	0.25	0.5006	0.249
	0.5	0.5038	0.511
	0.75	0.5019	0.7495
	1.0	0.5025	0.9955
	1.25	0.5031	1.2424

The first controller is based on a 16-bit ATmega328 (ATMEGA2560) processor from Microchip Technology (USA) with integer arithmetic and limited memory. The Arduino IDE environment provides the necessary libraries for processing standard C++ data types and performing mathematical operations with real numbers. Therefore, such operations are performed through separate subroutines. But the main limitation of this type of controllers is the small amount of RAM. Already for processing 300 data groups, a compiler message appears:

Sketch uses 9518 bytes (3%) of program storage space. Maximum is 253952 bytes.

Global variables use 6740 bytes (82%) of dynamic memory, leaving 1452 bytes for local variables. Maximum is 8192 bytes. Low memory available, stability problems may occur.

Testing showed that the processor capabilities are not enough for such a large amount of data.

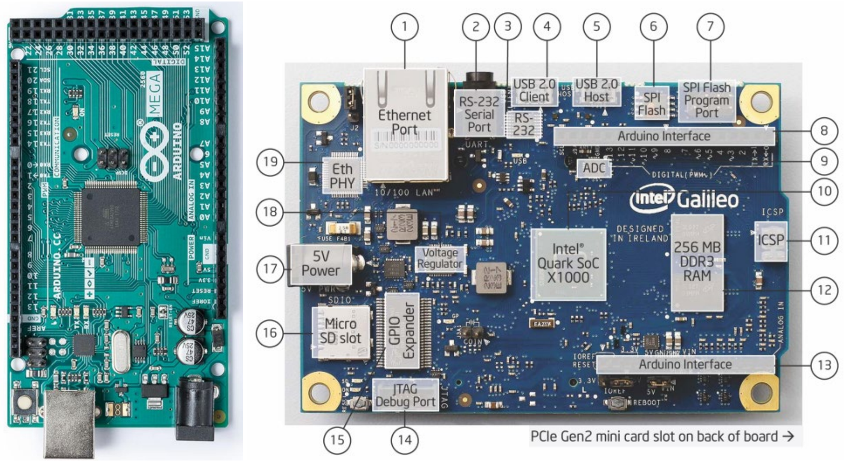
Therefore, this same program was compiled for the second type of controller, which is based on a 32-bit Intel® Quark™ SoC X1000 processor from Intel Corporation (USA), equipped with a mathematical coprocessor that includes support for real numbers in double format and has from 0.5 to 1 GB of RAM.

Using the Serial Plot tool, a graph of the output signal of the program was constructed, which calculates in turn the time constant (Fig. 6) or the damping coefficient (Fig. 7). The calculation in the program is performed with a step that corresponds to the time of data acquisition, while the display step in Serial Plot is selected according to the number of points stored in this tool (50).

Thus, the implementation of the algorithm for identifying the parameters of the pitch, height and linear translational channels in UAV control systems is quite possible. But for the proposed algorithm to work, it is necessary to use processors with sufficiently high performance and RAM.

This class of processors includes modern single-chip microcontrollers with 32-bit buses, a clock frequency of 40–400 MHz, a RAM volume of about 1 MB or more, for example:

1. STMicroelectronics STM32H743/753, clock frequency up to 400 MHz (ARM Cortex-M7), 1 MB SRAM – high performance, developed peripherals, support for Ethernet, CAN FD.
2. Microchip SAME70Q21, 300MHz (Cortex-M7), 512KB SRAM, cryptography support, CAN, USB, Ethernet.
3. Renesas RA6M5, up to 200MHz (Cortex-M33), 512KB SRAM, high security (TrustZone), IoT peripherals.
4. Texas Instruments TMS570LC4357, 300MHz (Cortex-R5F), 512KB SRAM, certified for security systems (automotive and industry).



a *b*

Fig. 5. Programmable controllers used to test the developed identification method: *a* – Arduino Mega 2560; *b* – Intel Galileo

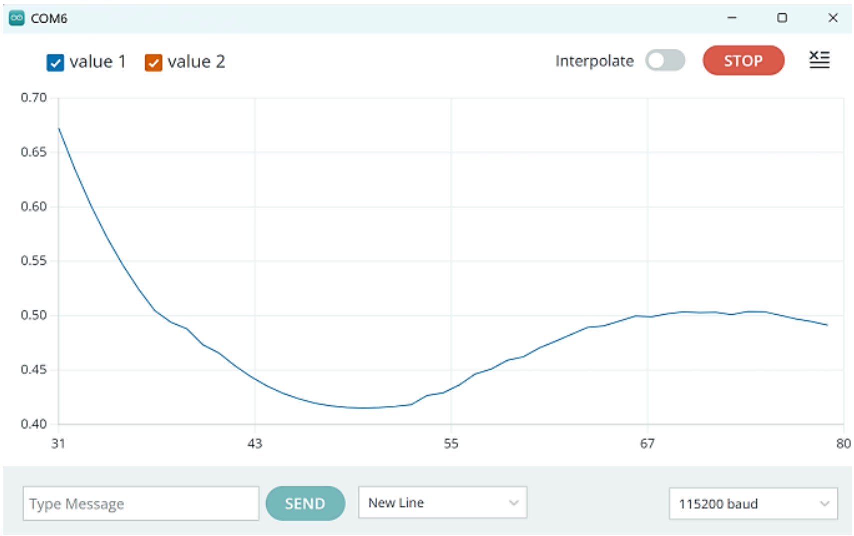


Fig. 6. Identification T with a time step of 0.05 s

Fig. 7. The last 50 identification points ξ with a step of 0.03 s

At the same time, the calculation procedures are performed by such processors quickly enough so as not to interfere with the solution of the main task – controlling the UAV movement.

3.4. Discussion

As a result of the analysis, it was found that the dynamics of individual UAV motion channels (pitch, height, translational motion) can be adequately described in the form of a normalized second-order dynamic link with parameters: time constant T, damping coefficient k_{cs} and static gain coefficient k. The obtained analytical dependencies show that the model parameters have a physical interpretation of mass-inertial characteristics with a system of the "mass-damper-spring" type. Moreover, the time constant T is determined by the inertial properties of the object; the damping coefficient k_{cs} characterizes the damping intensity, and the gain coefficient k reflects the static properties of the channel. Fig. 4 shows the time characteristics of the system response at different values of the damping coefficient. The main result for the analysis is the change in the speed and nature of the transient process when changing k_{cs}. The regularity of the influence of changes in mass-inertial characteristics when dropping a suspended load is established. In this case, a decrease in mass or moment of inertia leads to a decrease in the time constant, an increase in the damping coefficient; an increase in the object's response. The obtained dependencies are explained by a decrease in the inertia of the system, which leads to a faster response to the control effect. Unlike complex multidimensional models, the proposed approach allows the use of a compact second-order model with physically interpreted parameters. Unlike approaches [1–6], which use complex optimization or stochastic methods, the proposed model provides sufficient accuracy with significantly lower computational complexity. An algorithm for identifying the parameters of a second-order model based on experimental input-output data has been developed based on reducing the differential equation to a linear regression form and estimating the parameters by the least squares method. Table 2 shows the results of parameter identification for different values of the damping coefficient. The results show a high level of compliance of the identified parameters with the specified ones. It was established that the relative error in determining the time constant does not exceed 0.8%; the relative error of determining the damping coefficient does not exceed 1.2%. The high accuracy of identification is explained by the use of the developed analytical method and pre-processing of data. The proposed method does not require complex optimization procedures or matrix libraries, which significantly distinguishes it from classical identification methods.

Unlike classical or metaheuristic algorithm methods, the proposed approach provides high accuracy with significantly lower computational complexity.

A simplified algorithm for implementing the identification method for programmable controllers has been developed. The results of experimental verification have shown that the algorithm can be implemented without the use of matrix operations, the calculations are reduced to the operations of summing and solving a system of linear algebraic equations, and the possibility of operating in a mode close to real time is provided. When testing on controllers, it was found that for Arduino Mega2560 (8/16-bit) there are limitations in the amount of RAM, while for Intel Galileo Gen 2 (32-bit) stable operation of the algorithm is ensured. The obtained results are explained by the difference in the performance and architecture of processors. The proposed implementation allows the method to be applied in embedded systems without the use of specialized software.

Comparing the obtained identification results with the known approaches analyzed in the literature review, it is possible to note that in modern researches of UAV dynamics identification, methods focused on flight data processing, construction of complete spatial models or refinement of parameters in a closed control loop are mainly used. In particular, in the works [1, 10, 11] approaches to the identification of multirotor UAVs based on onboard sensor data are considered, including trajectory reconstruction procedures, parameter estimation in the time domain and the use of the extended Kalman filter. The proposed approach is based on the use of a second-order model, and for identification only data on the operator's motor skills and the corresponding aircraft motion channel are required. Comparing the algorithms for identifying quadcopter parameters in [1], it can be noted that the considered method requires less computational capabilities of microcontrollers, since only the operator's input signal $u(t)$ and the model's output response $y(t)$ are used. In [1], a combination of trajectory calculation and identification in the time domain is used to refine the parameters. This ensures the accuracy of model parameter estimation, but requires complex data processing algorithms.

The results with metaheuristic identification methods, in particular particle swarm optimization and other optimization algorithms [7, 8, 13, 14] require a separate comparison. Such methods are universal and allow minimizing complex quality criteria between experimental and model trajectories. However, their disadvantages are iterativeness, dependence on initial settings, the need for a significant number of calculations, and the complexity of direct implementation in simple programmable controllers. In contrast, the proposed algorithm is reduced to calculating scalar sums and solving a system of two linear algebraic equations. Therefore, it has a lower computational complexity and better meets the requirements of implementation in programmable controllers.

Compared with online identification methods based on EKF [11], sparse regression [27] or closed-loop/subspace identification [29, 30], it is clear that the proposed approach is simpler and more specialized. It does not claim to be a universal description of the entire UAV dynamics, since it is focused on a second-order model for a separate motion channel. At the same time, it is precisely this limitation that makes the method convenient for practical use. The model parameters have a clear physical meaning, and the algorithm itself does not require complex matrix libraries of high dimensions. This is important for systems where, along with accuracy, simplicity of implementation, repeatability of calculations and the ability to work with limited computing resources are required. A comparison with deep learning methods [15] shows that the proposed procedure does not require a large set of training data and preliminary training of the neural network. Neural network methods can reproduce the dynamics of the object quite accurately, but their results are not always easy to explain from a physical point of view. In addition, such approaches require significant computational resources. In the proposed procedure, the parameters T and k_{cs} are determined directly from the differential equation of the model, so the result obtained is understandable.

Researches that analyze the dynamics of the pilot-operator in stochastic conditions [16] do not involve building a complete model of the "human-operator-UAV" system. The main attention is focused on the fact that the operator signal is used as a real input influence to identify the parameters of the UAV model. This is a difference of the proposed approach, because it allows to take into account the actual nature of the operator's control and does not complicate the model with a description of the human-operator dynamics.

Generalizing the comparison with known works, it is possible to conclude that the proposed approach is inferior to more complex methods in terms of versatility and completeness of the description of the spatial dynamics of the UAV, but has significant advantages in terms of simplicity of implementation, physical interpretability of parameters and suitability for use in programmable controllers. This determines its practical value in the tasks of rapid identification of parameters of a separate UAV motion channel based on experimental input-output data.

The limitations of research are the assumption of the adequacy of the second-order model, which limits its application in cases of significantly nonlinear or multi-coupled dynamics. The accuracy of identification depends on the quality of the experimental data. The results obtained are based on computer simulation data with an operator in the control loop, which requires additional verification in full-scale experiments for practical implementation.

Further research should be directed at expanding the method to nonlinear models and increasing the noise immunity of the algorithm.

4. Conclusions

1. The structure of the UAV motion channel model in the form of a second-order dynamic link with parameters T, k_{cs}, k is substantiated. It is established that a decrease in mass or moment of inertia leads to a decrease in the time constant and an increase in the damping coefficient, which ensures acceleration of the object dynamics. This confirms the adequacy of the model for control system synthesis problems.
2. An algorithm for identifying model parameters based on the transformation of the differential equation into a linear regression form has been developed. According to the results of 500 experimental tests conducted with the participation of 20 operators, it was established that the relative identification error does not exceed 0.8% for the time constant and 1.2% for the damping coefficient, which indicates high accuracy of the method.
3. An identification algorithm adapted for programmable controllers has been developed, which does not require the use of matrix libraries and is based on simple algebraic operations. It has been experimentally confirmed that 32-bit controllers ensure stable operation of the algorithm in a mode close to real-time, which proves the possibility of its practical application in embedded UAV control systems.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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The research was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

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

Authors' contributions

Oleksiy Chornyi: Conceptualization, Formal analysis, Software, Data curation; ***Valerii Tytiuk:*** Data curation, Formal analysis; ***Victor Busher***: Funding acquisition, Investigation; ***Iurii Zachepa***: Resources, Software; ***Volodymyr Grabko***: Supervision; ***Andrii Romanets***: Methodology, Project administration; ***Yuliia Mala***: Validation; ***Dmytro Bilukhin***: Visualization; ***Mykola Babyak***: Writing – original draft, Resources; ***Olena Huliesha***: Resources, Writing – review and editing.

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Oleksii Chornyi, *Doctor of Technical Science, Professor, Department of Automatic Control Systems and Electric Drives, Kremenchuk Mykhailo Ostrohradskyi National University, Kremenchuk, Ukraine, ORCID: https://orcid.org/0000-0001-8270-3284*

Valerii Tytiuk, *Doctor of Technical Sciences, Professor, Department of Electromechanics, Kryvyi Rih National University, Kryvyi Rih, Ukraine, ORCID: https://orcid.org/0000-0003-1077-3288*

Victor Busher, *Doctor of Technical Sciences, Professor, Department of Electrical Engineering and Electronics, National University "Odessa Maritime Academy", Odesa, Ukraine, ORCID: https://orcid.org/0000-0002-3268-7519*

Yurii Zachepa, *Candidate of Technical Sciences, Associate Professor, Department of Automatic Control Systems and Electric Drives, Kremenchuk Mykhailo Ostrohradskyi National University, Kremenchuk, Ukraine, ORCID: https://orcid.org/0000-0003-4364-6904*

Volodymyr Grabko, *Doctor of Technical Science, Professor, Department of Computerized Electromechanical Systems and Complexes, Vinnytsia National Technical University, Vinnytsia, Ukraine, ORCID: https://orcid.org/0000-0002-4666-1758*

✉***Andrii Romanets,*** *PhD Student, Department of Electrical Engineering and Cyber-Physical Systems, Zaporizhzhia National University, Zaporizhzhia, Ukraine, e-mail: ivan.van.mi@gmail.com, ORCID: https://orcid.org/0009-0000-9893-8408*

Yuliia Mala, *Candidate of Technical Sciences, Associate Professor, Department of Computer Science and Software Engineering, University of Customs and Finance, Dnipro, Ukraine, ORCID: https://orcid.org/0000-0002-2539-4793*

Dmytro Bilukhin, *Candidate of Technical Sciences, Associate Professor, Department of Electric Railway Rolling Stock, Ukrainian State University of Science and Technologies, Dnipro, Ukraine, ORCID: https://orcid.org/0000-0002-2791-617X*

Mykola Babyak, *Candidate of Technical Sciences, Associate Professor, Department of Railway Transport, Lviv Polytechnic National University, Lviv, Ukraine, ORCID: https://orcid.org/0000-0001-5125-9133*

Olena Huliesha, *Candidate of Pedagogical Sciences, Associate Profes sor, Department of Electronics and Electronic Communications, Dniprovsky State Technical University, Kamianske, Dnipropetrovsk Region, Ukraine, ORCID: https://orcid.org/0000-0002-7512-5671*

✉*Corresponding author*