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CONTROL IN TECHNICAL SYSTEMS

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METHODOLOGY FOR UNPILOTED AIRCRAFT DYNAMICS CONTROL USING CORPORATE GAME THEORY AND MULTI-CHANNEL AERIAL IMAGERY

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ABSTRACT

Context. The increase in the number of wars in the modern world stimulates the progress of technological innovation, including the operation of drone systems and modern control systems. The research into mathematical simulations of pursuit, combined with methods of corporate differential games with dynamic constraints, can help throughout the development of the latest vehicle control systems in the civilian and military fields.

Objective. The study is intended to develop a methodology for using multi-channel satellite imagery data in combination with the calculation of unpiloted aircraft motion and dynamic deformations of its elastic elements in vehicle guidance systems derived from pursuit models in cooperative differential game theory.

Method. The methodological framework of the study consists in the integration of data from multi-channel aerospace images into the calculation of motion parameters and, based on this, the deformation of aircraft through the application of game theory methods and the development of advanced information systems to neutralize the opponent's counteraction. The employment of aerospace photography has emerged as an essential element of many modern technologies in remote vehicle control systems. Despite the lack of reliable vehicle control systems using aerospace photography, they are frequently used and are instrumental in saving countless lives. Meanwhile, aerospace photography is exposed to a large number of excitatory factors that make information on them is commonly misleading, preventing its direct and correct application. The main strategy for increasing the reliability of processing and analytical results of aerospace images in this technique relies on multichannel images, i.e., multiple images of a single object acquired at different radiation frequencies, from distinct positions, angles, or time of shooting. This technique implements nature-inspired strategies for optimal management, validated by wildlife evolution. The technology for processing multi-channel images and Integrating these results into vehicle management models remains underdeveloped and needs further refinement.

Results. The study's scientific novelty consists in establishing methodological foundations for utilizing data from multichannel aerospace imagery, computing unmanned aircraft dynamics within vehicle control systems, and developing advanced information technologies for optimal aircraft management. This approach is based on pursuit models in cooperative differential games and leverages neural network machine learning techniques.

Conclusions. The experiments validate the effectiveness of the proposed approach for enhancing the accuracy of processing and analyzing aerospace images. A methodology for developing vehicle control systems based on pursuit models has been established. Future research will concentrate on adapting the model to new datasets.

KEYWORDS: pursuit model, corporate differential games, multi-channel space images, optimal management.

ABBREVIATIONS

AIM is an aerial imagery;
CS are control systems;
DOF are degrees of freedom;
FEM is a finite element model;
FSI is a fluid-structure interaction;
GIS is a geoinformation system;
HCT is a hyper spherical transformation;

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HD is a high-definition;

HSV is a hue, saturation, value;

ISO is an International Organization for Standardization;

MCAI is a multi-channel aerial imagery;

NST is a neural style transfer;

PID is a proportional-integral-derivative;

PMG is a propeller-motor group;

PSNR is a peak signal-to-noise ratio;

RGB is a red, green, blue;

RPM are revolutions per minute;

SC and MC are single and multichannel, respectively;

SCAI is a single-channel aerial imagery;

SSIM is an index of structural similarity;

UAVs is an unmanned aerial vehicle;

VCS is a vehicle control system;

VGGNet is a convolutional neural network.

NOMENCLATURE

$\overrightarrow{e_{M_l}}$ are unit vectors;

$\overrightarrow{r_{M_l}}$ are vectors of the centers of the PMG;

$\overrightarrow{v_B}(t)$ is a linear velocity vector;

$\vec{F}(t)$ is a total of all forces applied to the copter;

$\vec{M}(t)$ is an aggregate of all moments exerted on the copter;

J_i is an objective function of *i*-th player;

$\vec{L}(t)$ is an angular momentum of the copter;

M_M is an engine reactive torque;

R_{IB} is a transformation matrices from system I to B;

$\vec{p}(t)$ is a momentum of the copter;

t_x is a time point at which the distance between the pursuer and the evading object is less than a certain threshold value $\varepsilon > 0$;

x_i are the x axes of the systems;

y_i are the y axes of the systems;

z_i are the z axes of the systems;

ω_{M_i} are rotation of PMG;

$f_p(x_p, u_p, t)$ is a dynamics functions for the predator;

$f_t(x_t, u_t, t)$ is a dynamics functions for the prey;

H is a Hamiltonian functional;

I is a stationary inertial system, connected to the Earth

B is a stationary inertial system, connected to the copter;

$I(t)$ is a tensor of inertia (the linear operator of the moment of inertia);

J_p is a payoff function;

J_t is a payoff function;

m is a mass of the copter;

t is a time;

$u_t(t)$ is a control vector of the pursuer, $u_t(t) \in U_t$;

$u_t{}^*$ is a control that minimizes t_x;

U_p, is a region of permissible controls of the predator;

U_t is a region of permissible controls of the prey;

$u_t(t)$ is a control vector of the evading object; $u_t(t) \in U_t$;

$u_t{}^*$ is a control that maximizes time t_x;

$V(x_p, x_t, t)$ is a cost function;

$x_p(t)$ is a position of the pursuer at time t in space, $x_p(t) \in R^n$;

$x_t(t)$ is a position of the prey at time t in space, $x_t(t) \in R^n$;

θ is a pitch;

σ_{color} is a parameter of denoising;

σ_{space} is a parameter of denoising;

φ is a roll;

ψ is an yaw/heading;

$x(t)$ is a vector of states of all players;

λ_p are the Lagrange multipliers;

$\omega(t)$ is a current angular velocity.

INTRODUCTION

MCAI refers to data obtained from satellites or UAVs that record electromagnetic radiation in multiple spectral bands. Each spectral channel highlights different physical characteristics of observed objects, enabling more detailed and nuanced analysis. Using multiple channels improves the accuracy of tasks such as object classification, change detection, and environmental monitoring.

To fully understand the complex processes occurring on the Earth's surface, integrating data from multiple sources is crucial. Modern information technologies provide the foundation for combining satellite imagery with other types of data, such as ground-based observations, statistics, and others. As data collection technologies advance, the volume of information received from satellites grows rapidly, necessitating the development of new methods and algorithms for processing, analyzing, and visualizing this data, often in real time. Using information technologies to analyze satellite imagery facilitates more informed decision-making in areas such as ecology, agriculture, urban planning, and others.

The ongoing war in Ukraine has significantly altered the global geopolitical landscape, impacting international satellite technology, aviation, and defense. This has accelerated the development of advanced technologies, particularly UAVs and next-generation weapons systems. Modern warfare increasingly relies on technological integration, including the use of multichannel satellite imagery to improve the precision and effectiveness of air operations. In combat situations, rapid and accurate decision-making is critical to operational success. A multispectral artificial intelligence system, capable of collecting data in various spectral bands (optical, infrared, radar, etc.), is essential for reconnaissance, surveillance, and air force coordination.

AIM has become a key component of modern CS and remote sensing technologies. The study of mathematical pursuit models, along with cooperative differential game

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methods, is contributing to the development of new control systems for both civilian and military applications.

The object of study. The study focuses on a methodology that integrates multichannel satellite imagery data with the computation of unmanned aircraft motion and dynamic deformations of its elastic components within vehicle control systems, utilizing pursuit models in cooperative differential games.

The purpose of the work is to design and assess the effectiveness of vehicle control systems based on pursuit models in cooperative differential games.

1 PROBLEM STATEMENT

The pursuit problem in differential games aims to model a situation in which one player (the pursuer or predator) seeks to shorten the distance to another player (the evader or prey) and carry out the so-called “interception”. The mathematical formulation of the pursuit problem is based on a system of differential equations that describes the dynamics of the movement of the pursuer and the evading object. The motion of the predator and prey is described by the following systems of differential equations

$$\begin{cases} \dfrac{dx_p}{dt} = f_p\left(x_p, u_p, t\right), \\ \dfrac{dx_t}{dt} = f_t\left(x_t, u_t, t\right), \end{cases}$$

where f_p and f_t determine the dependence of the velocity on the current position and player controls.

The controls u_p and u_t are chosen by the players in real time in order to achieve their goals. The criterion for successful pursuit is reaching a time point t_x

$$\left\| x_p\left(t_x\right) - x_t\left(t_x\right) \right\| \le \varepsilon.$$

The predator seeks to minimize the time t_x, and the prey seeks to avoid this state as long as possible or to prevent its achievement at all. The evading object, accordingly, seeks to maximize time t_x. To formalize the goals of each player, we introduce payoff functions J_p and J_t. Let the payoff functions be of the form

$$J_p = -t_x, \quad J_t = t_x.$$

The pursuit problem is an optimization problem, where players choose controls u_p and u_t in order to optimize their payoff functions.

The pursuer seeks to choose a control u_p* that minimizes the time to reach t_x, the evading object chooses control u_t* that maximizes time t_x

$$u_p^* = \arg \min_{u_p \in U_p} J_p, \quad u_t^* = \arg \max_{u_t \in U_t} J_t.$$

These optimization conditions form a saddle point in the pursuit problem, which is a solution within the framework of the differential game.

To find optimal strategies, one can use the Bellman dynamic programming method, which allows solving the problem using the cost function $V(x_p, x_t, t)$ – that is, the minimum time required to achieve pursuit under optimal actions.

Another method – Pontryagin’s maximum principle – involves constructing a Hamiltonian functional to determine optimal controls in the form

$$H = \lambda_p \cdot f_p\left(x_p, u_p, t\right) + \lambda_t \cdot f_t\left(x_t, u_t, t\right),$$

where λ_p and λ_t are the Lagrange multipliers. The maximum principle requires maximizing or minimizing this functional, which allows finding the controls (t, u_p) and (t, u_t) that are optimal.

2 REVIEW OF THE LITERATURE

The analysis of MCAI is a dynamically developing field and is actively studied in scientific circles. One of the main areas of use of MCAI is military intelligence. These images provide information about the location of enemy objects, their activity and the state of infrastructure. For example, studies [1] demonstrate that infrared satellite images allow you to detect hidden objects, such as camouflaged equipment or shelters, even in difficult weather conditions. MCAI is the basis for strategic planning of military operations. According to [2], these images are used to assess the suitability of the terrain for the deployment of equipment, build troop movement routes and predict possible scenarios for the development of combat operations. For example, infrared images can be used to detect heat sources, such as vehicle engines, which allow you to predict enemy movements. The work [3] shows how the use of multispectral satellite images improves coordination between units, reducing the risks of underestimating enemy actions. Optical satellite imagery, as noted in [4], is used to create high-precision cartography that can be integrated into the navigation systems of unmanned aerial vehicles. This allows them to ensure their precise orientation on the terrain and automatically perform combat missions. The operation of aircraft, especially in war conditions, depends on the accuracy of navigation, obstacle avoidance, and autonomous decision-making. UAVs provide these capabilities by integrating satellite data with UAV control systems. The study [5] examined methods for combining satellite data with machine learning algorithms for automatic recognition of objects in images. This allows UAVs to identify targets in real time. The study [6] demonstrates how radar satellite imagery allows UAVs to operate in poor visibility conditions, such as at night or during heavy rain. These images provide detailed information about the terrain and possible obstacles.

The use of MCAI for UAV control in war conditions, where speed of decision-making and accuracy are critical,

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is accompanied by a number of technical, organizational and technological problems, the solution of which is of paramount importance. One of the main problems is the technical limitations associated with the quality and speed of data acquisition. The study [7] indicates that high-resolution satellite images have significant transmission delays, which makes their use for real-time applications in conditions of active combat operations difficult. Another problem is the limitation of the spectral range. According to [8], some types of images (for example, infrared or radar) are less effective in certain conditions, such as thick fog or complex terrain. This limits their application in different climatic zones and natural conditions.

MCAI requires complex processing for integration with aircraft control systems. Studies [9] indicate that current processing algorithms cannot always provide accurate object recognition in conditions of high dynamics of combat operations. In addition, the large amount of data creates storage and transmission problem. As noted in [10], the volume of multi-channel images significantly exceeds the capabilities of operational transmission through military communication channels. This limits the speed of access to critical information. Modern research demonstrates that the latest technologies, such as artificial intelligence and big data processing, significantly increase the efficiency of using MCAI. In [11], methods were proposed for combining data from satellites with reconnaissance data from ground sensors, which allows creating a single information picture of the combat situation. Research [12] shows that predictive analysis technologies allow using satellite data to predict enemy movement and possible scenarios, which greatly facilitates the work of command in a rapidly changing situation.

The integration of MCAI into aircraft control systems is also accompanied by a number of problems. As noted in [13], many UAV control systems have limited compatibility with modern satellite data processing platforms. Another challenge is the delay in data transmission. Work [14] demonstrates that even small delays can cause failure of autonomous control systems, which is critical in a rapidly changing combat environment.

In military conflicts, the use of satellite data is associated with the risks of cyberattacks. According to [15], satellites and communication channels are often the targets of attacks, which can lead to interception or distortion of data. These risks significantly complicate the integration of multi-channel images into combat systems. In [16], the problem of data accuracy is discussed, in particular, the possibility of distortion due to interference or intentional interference. This creates additional difficulties for real-time decision-making.

The use of MCAI to control aircraft in war conditions is one of the key technologies that significantly increases the efficiency and accuracy of military operations. The integration of this data into UAV control systems, in combination with artificial intelligence technologies and the development of predictive analysis methods, opens up new opportunities for modern warfare. The problems of using MCAI to control aircraft are multifaceted and cover technical, organizational and cybersecurity aspects. Addressing these challenges requires an integrated approach that includes improving data processing technologies, enhancing cybersecurity, and creating universal platforms for integration with aircraft. Further research in this area is key to improving the effectiveness of satellite imagery in modern military operations and will contribute to the improvement of military technologies and their adaptation to the needs of modern conflicts.

The study of vibrations in UAV structures is a critical research area due to the need for reliability, structural integrity, and stability under dynamic loads. A central technique is modal analysis, which enables the determination of a structure’s natural frequencies and vibration modes. In [20], a finite element model (FEM) of a blended wing-body UAV was created in COMSOL to perform this analysis. The study determined the primary resonance frequencies and the associated deformation patterns of the airframe.

To reduce vibrations during operation, various vibration dampers, including additively manufactured ones, are actively researched. In [18], the authors designed and fabricated dampers for a single-rotor UAV, demonstrating improved vibration resistance and structural reliability.

Another important area is the analysis of harmonic response to external periodic forces. In [19], the dynamic behavior of the F450 quadcopter frame was analyzed. The study revealed resonance frequencies that coincided with motor RPMs, which are crucial to avoid destructive oscillations.

More comprehensive studies, such as [20], focus on the interaction between aerodynamic forces and structural dynamics (Fluid-Structure Interaction, FSI), as well as on modeling the dynamic reliability of multirotor UAVs under operational conditions.

Vibration protection of payloads is another important topic. In [21], a rubber T-shaped vibration damper was developed and tested for a UAV-mounted radar system. Both modeling and experimental results confirmed their effectiveness in reducing harmful vibrations.

In [22], static and modal analyses were carried out for UAV structures made of composite materials. The results demonstrated that material selection and lamination patterns significantly affect the vibration characteristics of the airframe.

Several studies also explore the experimental and numerical analysis of multirotor frames. In [23], vibration measurements were used to identify critical zones with high oscillation amplitudes and to provide design recommendations to improve stiffness and reduce resonance.

Sources also provide valuable insight into the modal analysis of composite structures. For example, [24, 25] present numerical and analytical methods for evaluating the dynamic characteristics of thin-walled elements and composite shells. In [26], a student thesis provides a detailed strength and vibration analysis of a swept-wing UAV using simplified force models.

In summary, there is a wide body of research covering various aspects of UAV vibration analysis, yet further

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studies are needed to address non-linear effects, complex aerodynamic loading, and real flight conditions.

3 MATERIALS AND METHODS

In corporate differential games, the pursuit problem models the process of interaction between several players who seek to achieve their goals in a dynamic environment. It is based on a mathematical formulation that takes into account the objective functions, constraints, and dynamics of the players' states. In military settings, these players can be represented by the following entities:

– own forces (aircraft control, resource optimization, task execution);

– opponent (location, actions, strategy prediction);

– environment (geography, weather conditions, infrastructure).

The main tasks that are solved by solving corporate differential games in these conditions are as follows:

1. Determining the optimal route of the aircraft, taking into account risks.
2. Maximizing the performance of the combat mission while minimizing losses.
3. Reaction to changes in the dynamic environment.

In the game, each player has his own state, described by the vector variable $x_i(t)$, where t is time. The strategies of the players are given by their control $u_i(t)$. The state of the system is described by the vector of states of all players

$$x(t)=\left[x_1(t),x_1(t),\cdots,x_N(t)\right].$$

The system evolves according to a system of differential equations

$$\frac{dx_i}{dt}=f_i\left(x_1(t),\cdots,x_N(t),u_1(t),\cdots,u_N(t)\right),$$

where f_i is a function that takes into account the interaction between players.

Each player seeks to maximize or minimize his objective function

$$J_i=\int_0^T g_i\left(x_1(t),\cdots,x_N(t),u_1(t),\cdots,u_N(t)\right)dt,$$

where g_i describes the gain or loss of the i-th player.

Real-world constraints on the system, such as the location of the impact zones, the availability of resources, or the technological limits of the UAV, can be expressed by equations or inequalities of the form

$$h_j\left(x_1(t),\cdots,x_N(t),u_1(t),\cdots,u_N(t)\right)\le 0,\ \ j=\overline{1,M}.$$

Since the constraints are dynamic and connect the states of all players, they allow taking into account new information about the movement of opponents. This is the main thing when constructing a solution to the variational problem of finding the optimal control and trajectory of the aircraft. It should be noted that the found price of the game reflects the guaranteed win (or loss) of the player regardless of the actions of the opponents. Therefore, the solutions of the game can be used to build a neural network to find the necessary values of the parameters and the initial state of the aircraft that would guarantee the completion of the task.

The solution of the corporate game is achieved not at the saddle point, but under conditions of achieving equilibrium, for example, Nash. Nash equilibrium defines a state in which no player can improve his position by changing his strategy if the strategies of others remain unchanged. This approach ensures stability in decision-making by players. The optimization problem can be written as follows: maximize the objective function J_i for all i, subject to the system of differential equations and the constraints on the system.

Modern military conflicts require high-precision data analysis and real-time operational decision-making. Multi-channel satellite imagery provides basic information for a more accurate determination of limitations in differential games. Aircraft (drones, airplanes, helicopters) perform critical tasks, including reconnaissance, logistics, combat support, and situation monitoring. Multi-channel satellite imagery is a unique source of data that can be used to ensure effective aircraft control. In this context, the methodology based on corporate differential games allows us to take into account the dynamic interaction of various factors and opponents. Multi-channel satellite imagery allows us to obtain information about the state of the terrain (relief, detection of shelters, obstacles), the dynamics of its changes (destruction of objects, water spills). Of particular importance is the ability to obtain critical information about the location of enemy forces (detection of vehicles, equipment, concentration of forces, monitoring of their movements). They can also be used to assess weather conditions (clouds, winds, soil moisture), predict changes in the external environment. These data are integrated into corporate differential game models for scenario prediction and decision-making.

Calculating drone vibrations involves dynamic analysis of its frame, propellers, and motors, as well as accounting for external factors (wind, interference), and using sensors (accelerometers, gyroscopes) for stabilization. To minimize vibrations, flight control systems (flight controllers) are used, which process sensor data and adjust motor speed, as well as built-in PID controllers, which maintain drone stability in the air.

The vibration calculation and minimization stages proceed in the following order. First, a dynamic simulation of the structure is performed. A mathematical model is created that takes into account its mass, component arrangement, frame rigidity, and aerodynamic characteristics. Next, external influences are analyzed: how vibrations from the motors and propellers affect the overall structure of the drone, as well as how external forces (wind) cause vibrations, are studied.

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The next step involves collecting data from sensors (gyroscopes and accelerometers). These sensors measure the drone's angular velocity and linear acceleration in real time, providing information about its current position and vibrations. Flight control systems are active throughout the entire flight. The "brain" of the drone is the flight controller, which receives data from sensors and, in accordance with preset control algorithms, regulates the motor speed to stabilize and maintain the desired trajectory. Built-in PID controllers process the drone's position data and adjust the propeller speed. They minimize deviations from the desired position, quickly responding to any vibrations.

Calculating the parameters of external influences determines physical design and component selection. Frame rigidity is determined first. Using strong and lightweight materials for the drone frame reduces vibration. Next, the propellers are balanced. Careful propeller balancing reduces their vibration load on the drone structure. Mounting the motors on special vibration-damping elements helps reduce vibration transmission to the drone frame.

Thus, calculating drone vibrations is a complex task that combines dynamics, aerodynamics, and electronics. The flight control system, working in conjunction with sensors, constantly adjusts the motors to compensate for any vibrations that occur, thereby ensuring the drone's stability in flight.

After calculating the oscillations of the UAV's elements, new constraints on its movement are formulated based on the conditions for maintaining the structural strength of the UAV. These constraints are introduced into the system of equations for calculating the corporate differential game, thereby modifying the calculated optimal trajectory of the UAV. This creates a nonlinear process for calculating the optimal trajectory, dependent on the dynamic identification of new countermeasures based on the analysis of multichannel images and the calculation of nonlinear oscillations of the UAV's structural elements (Fig. 1).

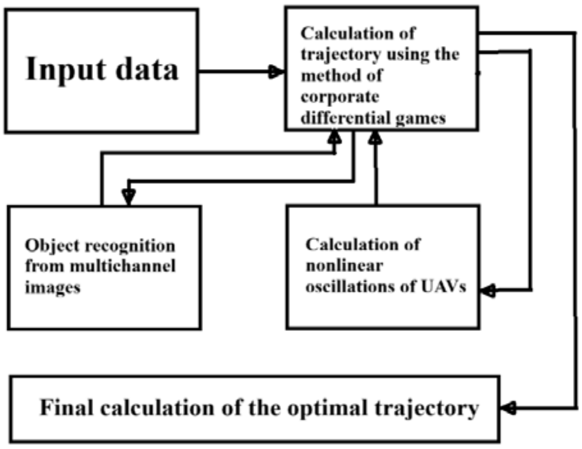

Figure 1 – A nonlinear process for calculating the optimal trajectory

Thus, a closed dynamic scheme for calculating the movement of a UAV using methods of corporate differential games has been created, which makes it possible to find the optimal trajectory of its movement, taking into account emerging threats and maintaining the strength and stability of the aircraft. The scheme makes it possible to construct an information system to support decisions on controlling an unmanned aerial vehicle without operator participation in the face of countermeasures and a changing situation in the flight zone.

4 EXPERIMENTS

An example of the application of the proposed method for processing multichannel images is shown in Fig. 2. Environment: Anaconda navigator, python 3.9, numpy, matplotlib, skimage, tqdm. The material for processing was captured from a DJI Mavic 3T drone.

1. Preliminary preparation:

– Calibration of sensors to reduce geometric errors;

– Bicubic interpolation to reduce to a single scale;

– Transition to HSV space for controlled adjustment.

2. Improving the quality of channels:

– HD channel: soft enhancement of details (unsharp mask: kernel 3×3, σ=1.0);

– Thermo channel: denoising (bilateral filter: d=9, σ_{color}=75, σ_{space}=75);

– Local brightness correction with contrast limitation.

3. Adaptive fusion:

– Exposure-fusion with weights 0.8/0.2 in favor of the visible channel;

– Increased local contrast through CLAHE (clip limit 1.5);

– Automatic setting parameters based on local estimates.

As can be seen from Table 1, the proposed method really increases the informativeness of the multispectral image, since the entropy value is higher compared to the input data.

Table 1 – Quantitative Values of Entropy

Image	Entropy Value
HD original	7.2719
ISO original	7.2932
Final result	7.4879

The results of the comparison according to quality criteria are shown in Table 2.

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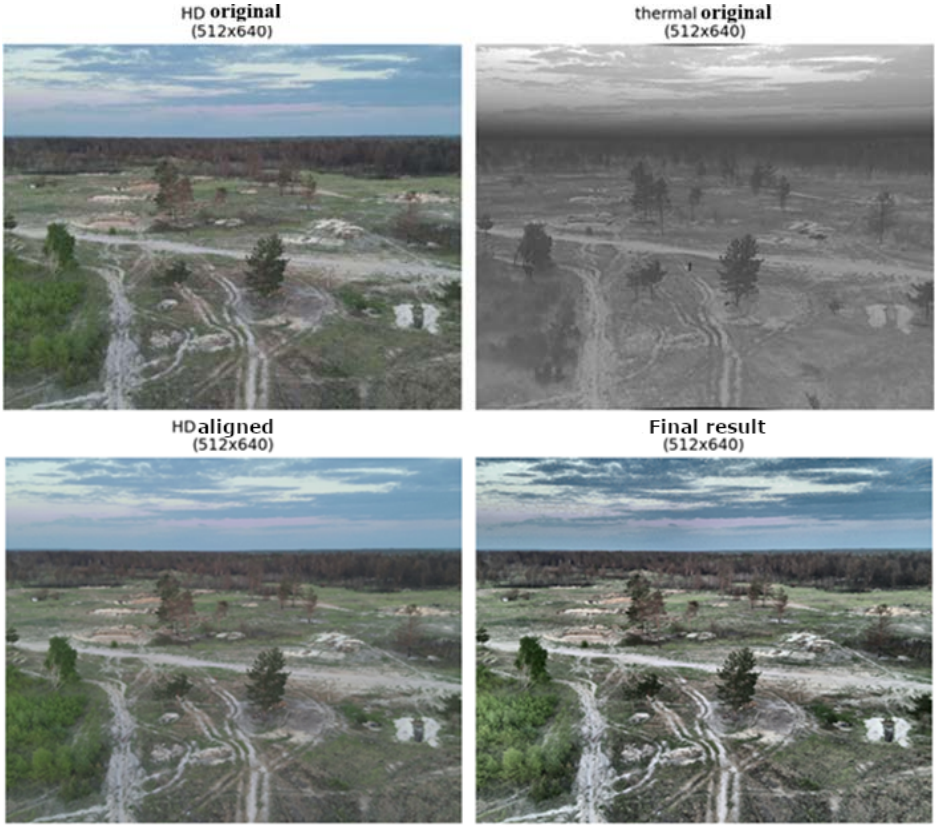

Figure 2 – Example of the application of the proposed method for UAV images

Table 2 – Comparison of merging methods

Metod	PSNR (dB)	SSIM	Sharpness
Simple weighing	19.70	0.61	57.7
Wavelet-fusion	19.70	0.63	57.7
Laplacian pyramid	17.30	0.58	50.6
Exposure-fusion (proposed)	29.20	0.78	85.9

5 RESULTS

The methodology for using multi-channel images is as follows.

1. Data collection using high-resolution satellites (WorldView, Sentinel, PlanetScope), which provide multi-channel coverage (optical, infrared, radar).

2. Image pre-processing: calibration and distortion correction, analysis of spectral characteristics to identify object types (vegetation, equipment, soil), and geological reference for accurate determination of coordinates.Before starting the analysis, it is necessary to perform pre-processing of images, for example, according to the method [27], which includes:

– geometry correction: elimination of distortions caused by satellite motion or atmospheric conditions;

– atmospheric correction: removal of the influence of the atmosphere on spectral data;

– brightness normalization: bringing images to a single scale for further analysis.

The most promising is the new technology developed in [28, 29] for geometric and spectral correction of high spatial resolution space images, taking into account the physical mechanisms of information fixation (Fig. 3).

To determine the effectiveness of the developed information technology, quantitative assessments of the quality of synthesized multichannel images were obtained, in particular, Shannon entropy, signal entropy, and others. The paper proposes a method of combining based on the use of batch wavelet basis construction [30] with decorrelation of primary species data, bicubic interpolation, conversion of RGB images to HSV format, and HCT [31]. The main stages of converting primary multichannel images are loading photogrammetric single-channel (SC) and multichannel (MC) images obtained from a satellite; then resampling the MC and reducing its dimension to the SC dimension based on bicubic interpolation. Next, geometric, radiometric, and contrast correction of the MC and SC are performed, and the image is converted from RGB format to the HSV color system. After replacing the brightness component of the multichannel image with the same component of the monochrome image, the inverse transformation of the image obtained at the previous stage from the HSV format to the RGB color system is performed. The resulting image will already have increased spatial resolution compared to the original image in natural colors. The next stage is the application of the developed method of geometric and spectral correction using the packet wavelet transform [30]. The inverse packet wavelet decomposition and obtaining the MC image in

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RGB format allows for the transformation of an 8-channel image, which, after interpolation into the hyper spherical color space of the NST and the inverse NST, leads to Fusion result. Analysis of the obtained results shows that using the proposed method increases the quality of the original space images and the quality of object recognition by 10–12%.

In the algorithm developed in this work for using MCAI to obtain the optimal CS, we will use a modified technology, replacing bicubic interpolation with the multidimensional Padé-type interpolation developed by us, which is more accurate and compact [31, 32] (Fig. 3).

3. Integration into the model: environmental modeling (building a digital map of the terrain using GIS systems), dynamics accounting (regular data updates for modeling enemy movement and terrain changes), risk prediction (assessment of dangerous zones). At this stage, it is advisable to create neural networks with machine learning algorithms and apply them for automation, classification and anomaly detection. We have developed a system of machine and deep learning of a neural network [33], which can also be used for the analysis of aerospace images (Fig. 3).

The initial level is a VGGNet, which identifies areas suspected of being dangerous in images. The main goal of this first level is to build a deep architecture with numerous convolutional layers for efficient feature extraction from images. This provides high recognition accuracy due to the specialization of the network for a certain type of image, thereby reducing the number of false positives. The deep learning model for optimal VCS is trained using a database, as shown in Fig. 3.

The second layer is designed to generate the optimal VCS. It performs classification of problem objects detected in the first layer and generates recommendations for further research and action protocols. In the deep learning process, the second layer uses the object data from the first layer together with metadata from the database.

Existing VCSs face significant problems in recognizing suspicious objects based on monochromatic data. Our neural network architecture for optimal VCS addresses this by combining multiple images in the first layer to improve the accuracy of object detection. These images are scaled to a single size that corresponds to their physical location on the surface, and a statistical matching criterion is applied to the object contour points with a given confidence level.

This deep learning model can perform in-depth analysis of large data sets and discover new information that it may not have been specifically trained to find.

It is important to use convolutional networks because the autonomous use of aircraft is assumed, and calculations must be performed directly on microprocessors located on board the device, and in an extremely short period of time. At the same time, the amount of machine memory is also limited, and it is necessary to use data compression and calculation acceleration methods [34, 35].

4. The previous steps allow for route optimization by calculating the pursuit model in corporate games: determining the best route for the aircraft taking into account the minimization of fuel consumption, bypassing areas of high risk of being hit by enemy means, which guarantees the maximum probability of completing the task regardless of the enemy's actions.

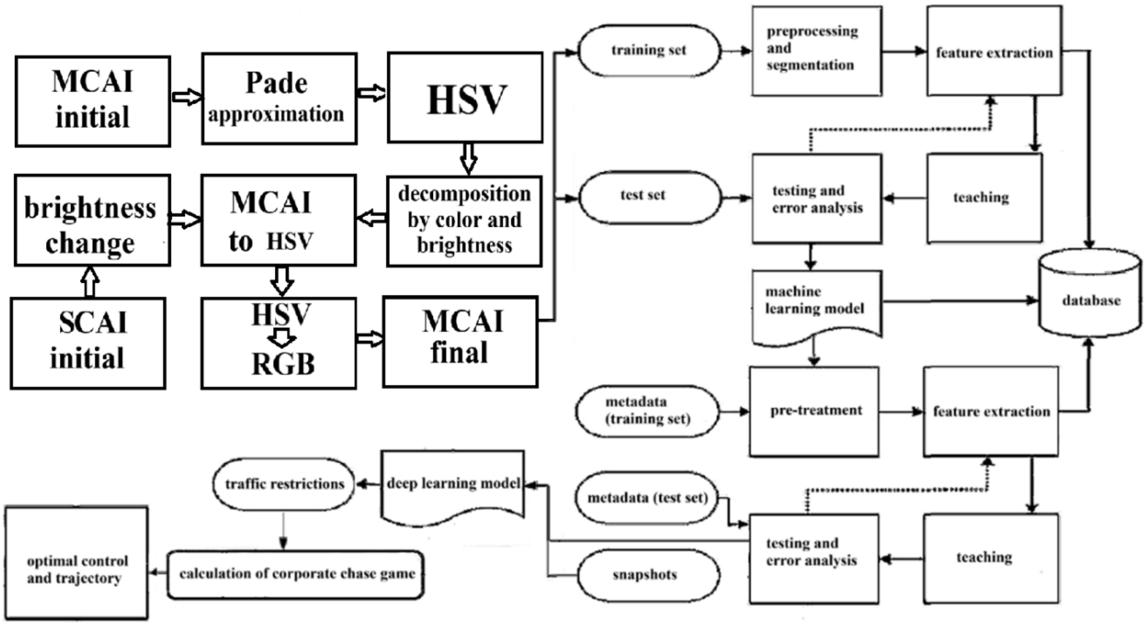

Figure 3 – Calculation of trajectory using the method of corporate differential games

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In the case of reconnaissance in combat conditions, when the aircraft is launched to monitor the territory, multi-channel satellite image data is integrated into the model as follows.

1. Enemy fortifications are detected through spectral analysis of the infrared range.
2. A safe route for the flight zone is determined.
3. The possibility of encountering enemy air defenses is predicted.

In the event of an aircraft attack on a strategic object, satellite data helps to determine the exact location of the target, simulate the enemy's reaction and ensure optimal task performance.

6 DISCUSSION

Calculating drone structural vibrations is based on dynamic analysis, which takes into account its mass, rigidity, and aerodynamic loads.

For simplified models, modal analysis is used to determine natural frequencies and vibration modes [36, 37]. For more accurate results, the finite element method (FEM) is used to model the structure as a system of coupled elements and calculate its response to various influences, such as motor vibrations or aerodynamic pressure [38, 39]. In this case, the reactive force from the drone's movement along the trajectory is used as the load, and this same force must be taken into account as an additional force in the previous calculations. This allows us to link the trajectory calculation using the corporate differential game method with the calculation of nonlinear vibrations of the UAV structure.

After calculating the oscillations of the UAV's elements, new constraints on its movement are formulated based on the conditions for maintaining the structural strength of the UAV. These constraints are introduced into the system of equations for calculating the corporate differential game, thereby modifying the calculated optimal trajectory of the UAV. This creates a nonlinear process for calculating the optimal trajectory, dependent on the dynamic identification of new countermeasures based on the analysis of multichannel images and the calculation of nonlinear oscillations of the UAV's structural elements (Fig. 6). Thus, a closed dynamic scheme for calculating the movement of a UAV using methods of corporate differential games has been created, which makes it possible to find the optimal trajectory of its movement, taking into account emerging threats and maintaining the strength and stability of the aircraft. The scheme makes it possible to construct an information system to support decisions on controlling an unmanned aerial vehicle without operator participation in the face of countermeasures and a changing situation in the flight zone.

CONCLUSIONS

The paper proposes a methodology for using multichannel images in corporate game theory for unpiloted aircraft dynamics control. Experimental analysis indicates that the proposed method delivers precise results. In particular, the methodology allows for route optimization by calculating the pursuit model in corporate games: determining the best route for the aircraft taking into account the minimization of fuel consumption, bypassing areas of high risk of being hit by enemy means, which guarantees the maximum probability of completing the task regardless of the enemy's actions. Similarly, the in the event of an aircraft attack on a strategic object, satellite data helps to determine the exact location of the target, simulate the enemy's reaction and ensure optimal task performance.

The scientific novelty of this work lies in establishing methodological foundations for utilizing multichannel aerospace imagery and computing unmanned aircraft dynamics within vehicle control systems, as well as developing advanced information technologies for optimal aircraft control. This approach is grounded in pursuit models within cooperative differential games and leverages neural network machine learning techniques.

The practical significance. The practical value of the proposed approach lies in its capacity to deliver precise and efficient vehicle control using UAV imagery for real-time motion monitoring, threat detection, and emergency response.

Prospects for further research. Future research directions include optimizing neural network architectures, expanding datasets, incorporating additional data sources, developing real-time processing methods, adapting to varying lighting and weather conditions, and segmenting video streams. Advancements in these areas will enhance the accuracy and efficiency of image-based vehicle control and broaden its potential applications across multiple industries.

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DECLARATIONS

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.

Authors' contributions: Dmytro Hryshchak: the method of training sample selection; Viktor Olevskyi: experimental study of training sample selection method; Yuliia Olevska: the method of training sample selection; Iryna Udovyk: the method of training sample selection.

Data availability: The manuscript has no associated data.

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APPENDICES

THE MODEL OF THE OBJECT'S DYNAMICS

Given an object [40] weighing approximately 10–25 kg, with 8 paired coaxial PMGs, arranged in a traditional quadcopter, hexacopter, or octocopter configuration on a rigid frame, with 8 engines or similar, and corresponding propellers. Assuming a lifting capacity of one PMG of approximately 2 kg at 50% throttle. We assume that the design of the apparatus has not yet been fully determined. Required: to design and implement a model of the object's dynamics.

The engine is modeled as a first-order inertial link, to which a given value of angular velocity is supplied as input, and the current value of angular velocity is supplied as output. The thrust force of the PMG is proportional to the square of the angular velocity

$$F_M(t) = C_T \cdot \omega^2(t),\ M_M(t) = C_0 \cdot \omega^2(t),$$

where $C_T = 2.02268 \cdot 10^{-4} N \cdot c^2, M_M \approx N \cdot m \cdot c^2$.

The multirotor apparatus is modeled as a solid body and is a rigid (non-deformable) frame of constant mass, symmetrical along three main axes, with the PMG attached to it in one plane, in which the center of mass of the apparatus is also located. The PMGs are located on eight beams and are rigidly fixed relative to the frame. The value $F_M(t)$, calculated in the PMG model is the magnitude of the force vector, always applied in a specific direction and at a specific point on the copter. During flight, this direction will change, but relative to the copter frame it remains constant.

Two coordinate systems are used: a stationary inertial system, connected to the Earth, and a moving system, connected to the copter. The coordinate systems are denoted by the letters I and B. The axes of the systems are directed: x_I – to the right, y_I – toward the observer, z_I – downwards, x_B – to the right along the beam of the first PMG, y_B – toward the observer along the beam of the third PMG, z_B – from top to bottom with the copter in normal orientation (Fig. 4). Then, in coordinate system B, the vectors of the centers of the PMG will be equal

$$\overrightarrow{r_{M_1}} = (l_1, 0, 0)^T,\ \overrightarrow{r_{M_2}} = \frac{1}{\sqrt{2}}(l_2, l_2, 0)^T,$$

$$\overrightarrow{r_{M_3}} = (0, l_1, 0)^T,\ \overrightarrow{r_{M_4}} = \frac{1}{\sqrt{2}}(-l_2, l_2, 0)^T,$$

$$\overrightarrow{r_{M_5}} = (l_1, 0, 0)^T,\ \overrightarrow{r_{M_6}} = \frac{1}{\sqrt{2}}(-l_2, -l_2, 0)^T,$$

$$\overrightarrow{r_{M_7}} = (0, -l_1, 0)^T,\ \overrightarrow{r_{M_8}} = \frac{1}{\sqrt{2}}(l_2, -l_2, 0)^T,$$

where l_1 is the beam length of the 1st, 3rd, 5th, and 7th PMGs, and l_2 is the beam length of the 2nd, 4rd, 6th, and 8th PMGs.

For the copter to be controlled along its course, in our case of the absence of engine torque, the thrust vectors of each PMG must be slightly deflected from the vertical direction, rotated around each beam by a small angle of about 5 degrees, and in different directions–even ones in one direction and odd ones in the other.

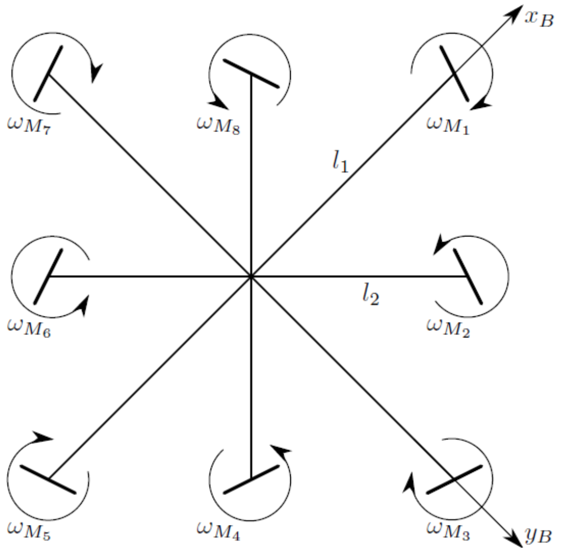

Figure 4 – UAV calculation scheme

If we denote this angle as γ, the unit vectors can be obtained in the following form

$$\overrightarrow{e_{M_1}} = (0, -\sin(\gamma), -\cos(\gamma))^T,$$

$$\overrightarrow{e_{M_2}} = \left(-\frac{\sin(\gamma)}{\sqrt{2}}, \frac{\sin(\gamma)}{\sqrt{2}}, -\cos(\gamma)\right)^T,$$

$$\overrightarrow{e_{M_3}} = (\sin(\gamma), 0, -\cos(\gamma))^T,$$

$$\overrightarrow{e_{M_4}} = \left(-\frac{\sin(\gamma)}{\sqrt{2}}, -\frac{\sin(\gamma)}{\sqrt{2}}, -\cos(\gamma)\right)^T,$$

$$\overrightarrow{e_{M_5}} = (0, \sin(\gamma), -\cos(\gamma))^T,$$

$$\overrightarrow{e_{M_6}} = \left(\frac{\sin(\gamma)}{\sqrt{2}}, -\frac{\sin(\gamma)}{\sqrt{2}}, -\cos(\gamma)\right)^T,$$

$$\overrightarrow{e_{M_7}} = (-\sin(\gamma), 0, -\cos(\gamma))^T,$$

$$\overrightarrow{e_{M_8}} = \left(\frac{\sin(\gamma)}{\sqrt{2}}, \frac{\sin(\gamma)}{\sqrt{2}}, -\cos(\gamma)\right)^T.$$

The following forces act on the copter.

1. Gravity. It is always directed downward along the z_I axis of the inertial coordinate system. Gravity is a constant value, dependent only on the copter's mass. The copter's mass is assumed to be constant and does not change.

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2. The thrust forces of the PMG. There are only 8 of them, they are directed along their directions, the magnitude of the forces is calculated depending on the angular velocity of rotation of the corresponding PMG.

3. Air resistance is modeled as having two components. Air resistance is directly proportional to air density, the square of the object's linear velocity in the air, and the characteristic cross-sectional area in the given direction (form factor). Wind force is an external disturbing force.

4. An external force or disturbance is an arbitrary external influence.

Taking into account the accepted assumptions, and the fact that the copter is modeled as a single rigid body, based on Newton's second law, we obtain two equations

$$\frac{d\vec{p}(t)}{dt}=\vec{F}(t),\quad \frac{d\vec{L}(t)}{dt}=\vec{M}(t).$$

The equations written in the inertial coordinate system are translated into coordinate system B associated with the copter, in which the terms of the right-hand side (their notation) are much more concise and convenient.

Substituting the values for the momentum and angular momentum of the copter into the given equations of Newton's second law, for the inertial coordinate system we obtain

$$\frac{d\vec{v_I}(t)}{dt}=\frac{1}{m}\vec{F_I}(t),\quad \frac{d\vec{\omega_I}(t)}{dt}=I^{-1}\left(\vec{M_I}(t)-\frac{dI_I}{dt}\cdot\vec{\omega_I}\right).$$

If the orientation of the copter is represented by three angles: roll φ, pitch θ, and yaw/heading ψ, and the transformation matrices from system I to B and back are denoted as R_{IB} and $R_{IB}=R_{IB}^{T}$, then any vector written for coordinate system I can be translated into coordinate system B, and vice versa, using multiplication of the corresponding matrix by a vector.

The coordinate system I is stationary, the copter flies and rotates relative to it, and along with it, the associated coordinate system B. By summing up all the forces that act on the copter, we can obtain the vector $\vec{F}(t)$ and the torque, and at each moment in time it is a vector with a well-defined length and direction in space.

Let us give the expression used for the rotation matrix from system I to B

$$R_{IB}=\left(R_{IBij}\right),\quad R_{IB11}=\cos(\theta)\cos(\psi),$$

$$R_{IB12}=\cos(\theta)\sin(\psi),\quad R_{IB13}=-\sin(\theta),$$

$$R_{IB21}=\sin(\varphi)\sin(\theta)\cos(\varphi)-\cos(\varphi)\sin(\psi),$$

$$R_{IB31}=\cos(\varphi)\sin(\theta)\cos(\psi)+\sin(\varphi)\sin(\psi),$$

$$R_{IB22}=\sin(\varphi)\sin(\theta)\sin(\psi)+\cos(\varphi)\cos(\psi),$$

$$R_{IB32}=\cos(\varphi)\sin(\theta)\sin(\psi)-\sin(\varphi)\cos(\psi),$$

$$R_{IB23}=\sin(\varphi)\cos(\theta),\quad R_{IB33}=\cos(\varphi)\cos(\theta).$$

Then we can write

$$\vec{v_B}(t)=R_{IB}\cdot\vec{v_I}(t),$$

and for the angular momentum

$$\vec{L_B}(t)=R_{IB}\cdot\vec{L_I}(t).$$

For the first of the dynamic equations, we obtain the following expression in the coordinate system B associated with the copter

$$\frac{d\vec{v_B}}{dt}=-\vec{\omega_B}(t)\times\vec{v_B}+\frac{1}{m}\vec{F_B}$$

and for the second equation, given that

$$\vec{L_B}(t)=I_B\cdot\vec{\omega_B}(t),$$

and since in a rotating fixed coordinate system the inertia tensor is constant and its time derivative is zero, and

$$\frac{d\vec{L_B}}{dt}=I_B\frac{d\vec{\omega_B}}{dt},$$

$$\frac{d\vec{\omega_B}}{dt}=I_B^{-1}\left(\vec{M_B}(t)-\vec{\omega_B}(t)\times\left(I_B\cdot\vec{\omega_B}\right)\right).$$

The state variables of the copter in this notation are two vector quantities (or six scalars) – the linear velocity vector and the angular velocity vector. Algebraically, this would be six variables – three projections of the linear velocity and three projections of the angular velocity. And we have a system of six first-order nonlinear equations written in Cauchy form.

Having obtained the values of the copter's velocities (first in the B system), they can be transformed using the inverse rotation matrix to the I system, integrated again, and obtained the coordinate values and, consequently, the position of the object in space, in the inertial coordinate system.

Let's designate with indices: M – the work of engines, only in terms of the thrust force created and the moments from it, D – the force of air resistance (together with the wind), O – external disturbance

$$\vec{F_B}(t)=\vec{F_M}(t)+\vec{F_D}(t)+\vec{F_O}(t)+m\cdot g\cdot R_{IB}\cdot\vec{e_{Iz}},$$
$$\vec{M_B}(t)=\vec{M_M}(t)+\vec{M}(t)+\vec{M_O}(t).$$

Let's write out what the terms are equal to

$$\vec{F_M}(t)=C_T\cdot\sum_{k=1}^{8}\omega_{M_k}^{2}(t)\vec{e_{M_k}}(t).$$

Air resistance force

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$$\overrightarrow{F_D} = -0.5\rho \cdot C_D \cdot \begin{pmatrix} A_{yz} \cdot v_x \cdot |v_x| \\ A_{zz} \cdot v_y \cdot |v_y| \\ A_{xy} \cdot v_z \cdot |v_z| \end{pmatrix}.$$

We will write the moment of the thrust forces of the engines as

$$\overrightarrow{M_M}(t) = C_T \cdot \sum_{k=1}^{8} \overrightarrow{r_{M_k}} \times \overrightarrow{e_{M_k}} \cdot \omega_{M_k}^2(t).$$

Moment of air resistance

$$\overrightarrow{M_D} = -0.5\rho \cdot C_D \cdot \begin{pmatrix} A_{yz} \cdot v_x \cdot |v_x| \cdot l_x \\ A_{zz} \cdot v_y \cdot |v_y| \cdot l_y \\ 8A_{xy} \cdot v_z \cdot |v_z| \cdot l_z \end{pmatrix}.$$

In the most compact form, the obtained and solved dynamic equations look like this

$$\frac{d\overrightarrow{v_B}}{dt} = -\overrightarrow{\omega_B}(t) \times \overrightarrow{v_B} + \frac{1}{m}\left(\overrightarrow{F_M}(t) + \overrightarrow{F_D}(t) + \overrightarrow{F_O}(t)\right) + gR_{IB}e_{Iz},$$

$$\frac{d\overrightarrow{\omega_B}}{dt} = I_B^{-1}\left(\overrightarrow{M_M}(t) + \overrightarrow{M_D}(t) - \overrightarrow{\omega_B}(t) \times \left(I_B \cdot \overrightarrow{\omega_B}(t)\right)\right).$$

By integrating them and obtaining the values of the velocities in the B system, one can calculate the speed and orientation angles in the inertial coordinate system *I*

$$\overrightarrow{v_I}(t) = R_{BI} \cdot \overrightarrow{v_B}(t),$$

$$\begin{pmatrix} \dot{\varphi} \\ \dot{\theta} \\ \dot{\psi} \end{pmatrix} = W_{BI} \cdot \overrightarrow{\omega_B}(t).$$

In coordinate system B, we have two vector differential equations, which, when converted to projections (and scalar equations), yield six first-order nonlinear differential equations in six variables: three velocities and three angular velocities. This is a so-called 6DOF problem, i.e., a problem with six degrees of freedom. At first glance, one might think that since the copter has six degrees of freedom, there must also be six state variables (differential variables). But this is only apparent. In addition to velocities, we will also need to obtain coordinates (three linear and three angular position coordinates) – for which we integrate the velocities again.

To close the model, it is necessary to calculate and implement all the right-hand sides of the six main equations. Thrust force of propeller-motor groups $\overrightarrow{F_M}(t)$

$$F_{M_x}(t) = \frac{1}{\sqrt{2}}\left(-F_{M_2}(t) - F_{M_4}(t) + F_{M_6}(t) + F_{M_8}(t)\right) \cdot \sin(\gamma) + \\ +\left(F_{M_3}(t) - F_{M_7}(t)\right) \cdot \sin(\gamma),$$

$$F_{M_y}(t) = \frac{1}{\sqrt{2}}\left(F_{M_2}(t) - F_{M_4}(t) - F_{M_6}(t) + F_{M_8}(t)\right) \cdot \sin(\gamma) + \\ +\left(F_{M_5}(t) - F_{M_5}(t)\right) \cdot \sin(\gamma),$$

$$F_{M_z}(t) = \sin(\gamma) \cdot \sum_{k=1}^{8} F_{M_k}(t),$$

where F_{M_i} is the thrust force of the *i*-th PMG at the current moment in time.

The air resistance force $\overrightarrow{F_D}(t)$ in the absence of wind – the formulas are given above, the projections will be equal to

$$F_{Dx} = 0.5\rho \cdot C_D \cdot A_{yz} \cdot v_x \cdot |v_x|,$$

$$F_{Dy} = 0.5\rho \cdot C_D \cdot A_{zz} \cdot v_y \cdot |v_y|,$$

$$F_{Dz} = 0.5\rho \cdot C_D \cdot A_{xy} \cdot v_z \cdot |v_z|.$$

The force of gravity, projected onto the axes of the moving coordinate system, the term $g \cdot R_{IB} \cdot \overrightarrow{e_{Iz}}$ will be equal to

$$g \cdot R_{IB} \cdot \overrightarrow{e_{Iz}} = \begin{pmatrix} -\sin(\psi) \\ \sin(\varphi) \cdot \cos(\theta) \\ \cos(\varphi) \cdot \cos(\theta) \end{pmatrix}.$$

And the last term in the equation of the linear velocity of the copter

$$-\overrightarrow{\omega_B}(t) \times v_B = \begin{pmatrix} v_{Bz} \cdot \omega_{By} - v_{By} \cdot \omega_{Bz} \\ v_{Bx} \cdot \omega_{Bz} - v_{Bz} \cdot \omega_{Bx} \\ v_{By} \cdot \omega_{Bx} - v_{Bx} \cdot \omega_{By} \end{pmatrix}.$$

Let's consider the equation for moments and for calculating angular velocity

$$\overrightarrow{M_M}(t) + \overrightarrow{M_D}(t) - \overrightarrow{\omega_B}(t) \times \left(I_B \cdot \overrightarrow{\omega_B}\right).$$

The sum of the moments of the thrust forces of all the PMGs

$$M_{M_x}(t) = \left[\frac{l_2}{\sqrt{2}}\left(-F_{M_2}(t) - F_{M_4}(t) + F_{M_6}(t) + F_{M_8}(t)\right) + \\ +l_1\left(F_{M_7}(t) - F_{M_3}(t)\right)\right] \cdot \cos(\gamma),$$

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$$M_{M_y}(t)=\left[\frac{l_2}{\sqrt{2}}\left(F_{M_2}(t)-F_{M_4}(t)-F_{M_6}(t)+F_{M_8}(t)\right)+\right.$$
$$\left.+l_1\left(F_{M_1}(t)-F_{M_5}(t)\right)\right]\cdot\cos(\gamma),$$
$$M_{M_z}(t)=\sin(\gamma)\cdot\left[l_2\sum_{k=1}^{4}F_{M_{2k}}(t)+l_1\sum_{k=1}^{4}F_{M_{2k-1}}(t)\right],$$

where $F_{M_i}(t)$ is the thrust force of the *i*-th PMG at the current moment in time, l_1, l_2 are the force arms.

Moment of air resistance

$$F_{Dx}=-0.5\cdot\rho\cdot C_D\cdot A_{yz}\cdot\omega_{Bx}\cdot\left|\omega_{Bx}\right|\cdot l_x,$$
$$F_{Dy}=-0.5\cdot\rho\cdot C_D\cdot A_{zz}\cdot\omega_{By}\cdot\left|\omega_{By}\right|\cdot l_y,$$
$$F_{Dz}=-0.5\cdot\rho\cdot C_D\cdot A_{xy}\cdot\omega_{Bz}\cdot\left|\omega_{Bz}\right|\cdot l_z.$$

Vector product of angular velocity and the product of the tensor of inertia and angular velocity

$$-\overrightarrow{\omega_B}(t)\times\left(I_B\overrightarrow{\omega_B}(t)\right)=\begin{pmatrix}\left(I_{yy}-I_{zz}\right)\cdot\omega_{By}\cdot\omega_{Bz}\\ \left(I_{zz}-I_{xx}\right)\cdot\omega_{Bx}\cdot\omega_{Bz}\\ \left(I_{xx}-I_{yy}\right)\cdot\omega_{Bx}\cdot\omega_{By}\end{pmatrix}.$$

The input variables here are the engine thrust forces (calculated outside of these equations, depending on the current rotation speed of each PMG and its power characteristic), the external disturbance force and torque (specified by the user), and gravity. Wind/precession/reactive torque, or other effects, may also be involved – these are not considered in this article; for brevity, we've limited ourselves to engine thrust and gravity. The output variables are the accelerations, velocities, and position (coordinates) of the copter – accelerations and velocities in coordinate systems B and I, and position in system I.

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МЕТОДОЛОГІЯ КЕРУВАННЯ ДИНАМІКОЮ БЕЗПІЛОТНИХ ЛІТАЛЬНИХ СУДЕН З ВИКОРИСТАННЯМ ТЕОРІЇ КОРПОРАТИВНИХ ІГОР ТА БАГАТОКАНАЛЬНОЇ АЕРОЗЙОМКИ

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АНОТАЦІЯ

Актуальність. Збільшення кількості воєн у сучасному світі стимулює розвиток технологічних інновацій, зокрема функціонування дронових систем та сучасних систем керування. Дослідження математичних моделей переслідування у поєднанні з методами корпоративних диференціальних ігор з динамічними обмеженнями може сприяти розвитку найновіших систем керування транспортними засобами у цивільній та військовій сферах.

Мета. Дослідження спрямоване на розробку методології використання даних багатоканальної супутникової зйомки у поєднанні з обчисленням руху безпілотних літальних апаратів та динамічних деформацій їх еластичних елементів у системах керування транспортними засобами, що базуються на моделях переслідування в теорії корпоративних диференціальних ігор.

Метод. Методологічна основа дослідження полягає в інтеграції даних багатоканальної аерокосмічної зйомки у розрахунок параметрів руху та, на цій основі, деформацій літального апарату шляхом застосування методів теорії ігор і розробки сучасних інформаційних систем для нейтралізації контрдій противника. Використання аерокосмічної зйомки стало важливим елементом багатьох сучасних технологій у системах дистанційного керування транспортними засобами. Незважаючи на відсутність надійних систем керування транспортними засобами на основі аерокосмічної зйомки, вони широко застосовуються та відіграють ключову роль у збереженні багатьох життів. Водночас аерокосмічна зйомка піддається дії численних факторів збудження, що робить інформацію про неї часто недостовірною та перешкоджає її прямому та правильному використанню. Основна стратегія підвищення надійності обробки та аналізу аерокосмічних зображень у цій методиці базується на багатоканальних зображеннях, тобто на множині знімків одного об’єкта, отриманих на різних частотах випромінювання, з різних позицій, кутів або часу зйомки. Ця методика реалізує натхненні природою стратегії оптимального управління, перевірені еволюцією живих організмів. Технологія обробки багатоканальних зображень та інтеграція цих результатів у моделі керування транспортними засобами ще не повністю розроблена і потребує подальшого вдосконалення.

Результати. Наукова новизна дослідження полягає у створенні методологічних основ для використання даних багатоканальної аерокосмічної зйомки, обчислення динаміки безпілотних літальних апаратів у системах керування транспортними засобами та розробці сучасних інформаційних технологій для оптимального управління літальними апаратами. Підхід базується на моделях переслідування в корпоративних диференціальних іграх та використовує методи машинного навчання на основі нейронних мереж.

Висновки. Експериментальні дослідження підтверджують ефективність запропонованого підходу для підвищення точності обробки та аналізу аерокосмічних зображень. Було розроблено методологію створення систем керування транспортними засобами на основі моделей переслідування. Подальші дослідження зосередяться на адаптації моделі до нових наборів даних.

КЛЮЧОВІ СЛОВА: модель переслідування, корпоративні диференціальні ігри, багатоканальні космічні зображення, оптимальне управління.

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