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METHOD FOR PREDICTING UAV TRAJECTORIES AND YAW FOR INDUSTRIAL AUTONOMOUS MISSIONS IN A DYNAMIC ENVIRONMENT

This paper addresses the problem of predicting the trajectory and anticipatory evasion of an unmanned aerial vehicle (UAV) in industrial autonomous missions in a dynamic environment, subject to noise in navigation measurements and energy constraints, which pose risks of delayed or excessive maneuvering and increased deviation from the route. **Objective**. To develop and verify, using a simulation model, a method that ensures prediction-based obstacle avoidance with control of deviation from the reference trajectory and maneuvering energy consumption. **Tasks**. Formulate the architecture of the avoidance system; develop a predictor of future coordinates based on a recurrent neural network with long-term short-term memory; determine a method for assessing collision risk using a safety zone; implement a trajectory correction algorithm taking into account the “safety–deviation–energy consumption” trade-off; perform a comparative evaluation with baseline methods. **Methods**. Coordinate predictions are constructed based on time sequences of coordinates and motion parameters; collision risk is assessed by analyzing the intersection of the predicted trajectory with obstacle safety zones; trajectory correction is formalized as an optimization problem to select a maneuver that minimizes the total tracking error and the proximity penalty. The effectiveness was verified in a Python environment on standard trajectories (straight, circular, and polygonal) by comparison with pure tracking, line-of-sight, vector field, and nonlinear stabilization methods. **Results**. The proposed approach achieved the smallest mean deviation from the trajectory (14.95 m), the lowest maneuver energy consumption (72 conventional units), the highest tracking success rate (86.08%), and the highest overall productivity coefficient (0.494) among the algorithms considered; a trade-off was observed regarding the minimum distance to obstacles. **Conclusions**. The prediction-oriented evasion method improves the overall navigation efficiency in industrial mission models; further research involves field validation on real platforms and optimization of the predictor’s computational costs.

Keywords: unmanned aerial vehicle; industrial autonomous missions; trajectory prediction; obstacle avoidance; recurrent neural network; trajectory correction; energy efficiency.

Introduction

Unmanned aerial vehicles (UAVs) have become a standard tool in industrial autonomous missions, such as inspections of power lines and substations, monitoring of pipelines and tank farms, surveys of wind farms, monitoring of construction sites, quarries and industrial zones, as well as the rapid assessment of facility conditions following incidents. In these scenarios, the value of UAVs is determined not only by the quality of the data collected, but above all by their ability to fly predictably and safely.

This task is complicated by existing industrial environments, which are characterized by restricted flight corridors, complex obstacle geometries, local radio interference zones, and multipath effects, as well as a high level of dynamic activity from surrounding objects (equipment, vehicles, personnel). In practice, this translates into the need to simultaneously ensure high trajectory tracking accuracy, collision avoidance, controlled energy consumption, and system stability in the face of sensor errors.

In industrial missions, UAVs operate in environments where navigation measurements are often noisy, and the environment’s configuration can change during flight. The most common practical consequence is instability in position and trajectory estimates (e.g., coordinate oscillations), leading to unwanted corrective maneuvers, increased route deviation, and energy waste. Under such conditions, reactive approaches that correct motion only “after the fact” of a dangerous proximity can trigger delayed or excessive evasion, compromising both safety and mission efficiency.

An additional practical requirement for industrial scenarios is reproducible and energy-efficient behavior. The control system must ensure the minimization of unnecessary maneuvers and the maintenance of an acceptable distance from obstacles while keeping the UAV on the specified trajectory. This is particularly important for missions where flight time is a limited resource, and any increase in energy consumption directly reduces operational duration and diminishes route coverage.

Literature Review

In recent years, a number of reviews have been published that systematize algorithms for route planning, obstacle detection, and avoidance for UAVs. Work [1]

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presents a comprehensive classification of forecasting approaches and discusses the suitability of methods for remote sensing application scenarios. Review [2] focuses on obstacle detection and avoidance (ODA) and compares approaches based on obstacle type, sensor configuration, and mission environment. Additionally, in [3], recent comprehensive reviews highlight the trend toward integrating artificial intelligence with classical planners and the growing demands for computational efficiency and real-time robustness.

Summarizing these scientific works, it can be concluded that the issues of ensuring obstacle prediction and avoidance processes, as separate components of UAV mission execution algorithms, remain relevant. At the same time, for industrial autonomous missions, it is necessary to coordinate actions such as "state estimation", "forecasting", "decision-making", and "maneuvering" in the presence of noise and sensor data degradation.

Classical trajectory tracking methods are widely represented by approaches based on vector fields. Reference [4] is one of the fundamental sources where a vector field is used to asymptotically reduce the tracking error to zero for small UAVs. Further development in this direction [5] aims to combine trajectory tracking and obstacle avoidance with minimal deviation from the route. The strength of vector and geometric methods lies in the simplicity and predictability of control. However, in industrial environments with noisy coordinates and changing obstacle configurations, reactive corrections increase the amplitude of maneuvers and, consequently, energy consumption. This is why there is a growing need for anticipatory control and motion prediction.

Model Predictive Control (MPC) is a common paradigm for generating safe trajectories while accounting for system constraints. Classical MPC formulations for obstacle avoidance [6] demonstrate the ability to formalize the problem as an optimization over the prediction horizon. In applied inspection scenarios [7], MPC is combined with Simultaneous Localization and Mapping (SLAM) and employs path smoothing to reduce flight time and memory requirements. This indirectly impacts the mission's energy efficiency. Modern variants [8] also integrate safety barrier functions to handle dynamic obstacles. At the same time, MPC architectures depend on model quality and can be sensitive to sensor errors. Under unstable measurements, state errors translate into inadequate control decisions, and computational complexity may limit their use on low-power onboard systems.

To improve resilience to navigation signal degradation, approaches [9–11] based on Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) are being actively developed.

In particular, for the task of compensating for errors during GPS signal outages, hybrid models [10] have been proposed that combine prior noise suppression with CNN–LSTM forecasting. Another direction, discussed in [12, 13], involves the optimization and selection of LSTM component parameters in combination with adaptive variants of the Extended Kalman Filter to improve 3D positioning during GPS outages.

Additionally, the paper [14] investigates LSTM-based approaches for sensor fusion in orientation estimation tasks based on inertial measurements, which is relevant for UAVs under unstable positioning conditions. Overall, neural network filters demonstrate potential, but the key challenge remains reconciling data and physical constraints.

Predicting UAV trajectories over a time horizon is used as a tool for early conflict detection and proactive risk assessment. Paper [15] examines recurrent LSTM-based trajectory prediction in the context of detecting potential conflicts in low-altitude airspace. Concurrently, review and methodological works [16–18] have emerged, systematizing UAV trajectory prediction algorithms, including variants combining neural networks and filtering schemes. A practically significant limitation of this class of methods is the accumulation of errors over long horizons and dependence on the quality of input measurements, which brings the problem back to the need for robust filtering and adaptive selection of the prediction horizon.

Reinforcement learning is applied to obstacle avoidance tasks in both discrete and continuous action spaces. In [19], a DRL approach for obstacle avoidance is demonstrated, comparing different categories of algorithms in simulation environments. For large-scale 3D scenarios, approaches [20] with a "human-in-the-loop" mechanism are being developed, which improve training controllability and agent behavior consistency.

A common practical choice is Proximal Policy Optimization (PPO). Studies [21, 22] have been conducted where PPO is applied to autonomous UAV navigation in unknown environments.

Of particular interest are comparisons [23] of algorithms (e.g., PPO vs. Deep Q-Network) in obstacle avoidance tasks in 3D simulations.

For industrial inspection missions, the articles [24, 25] are noteworthy, as they are directly focused on infrastructure scenarios, in particular the LSTM–DDPG (Long Short-Term Memory – Deep Deterministic Policy Gradient) approach, validated in simulations and field tests.

At the same time, it should be noted that while the DRL approach provides high adaptability, it often requires a significant number of training episodes and demonstrates sensitivity to input data. This is precisely why the role of hybrid approaches is growing in engineering systems, where learning complements, rather than replaces, stabilizing control logic and safety control [26, 27].

A separate body of work addresses energy constraints and resource-aware mission planning. In particular, the paper [28] proposes an energy-efficient coverage route planning method, where energy limits are an explicit constraint during route generation. Concurrently, data-driven models [29] for predicting performance degradation and energy consumption are being developed, which are crucial for estimating flight time reserves. In the context of industrial missions, this reinforces the need to minimize "unnecessary" maneuvers that may be caused by the instability of navigation measurements and reactive obstacle avoidance.

As can be seen, most of the approaches considered focus on isolated components: route planning, obstacle avoidance, data filtering, or adaptive control. Against this backdrop, systemic gaps emerge, such as insufficient coordination within a unified loop for state estimation, trajectory prediction, and trajectory correction for noisy navigation measurements. Furthermore, there is insufficient attention to energy consumption as a metric for evasion quality. This is particularly true in scenarios where smooth behavior and maneuver reproducibility are required for industrial missions.

Objectives and Contribution

The objective of this study is to develop a method for predicting UAV trajectories and deviations for industrial autonomous missions in dynamic environments under conditions of noisy navigation measurements. The proposed approach is geared toward scenarios in which the navigation decision must be robust to instability in coordinate estimates, and the visual channel (camera) is not considered a critical prerequisite for decision-making during maneuvering.

Main research objectives

1. Develop a method for predicting UAV trajectories based on RNN/LSTM for proactive obstacle avoidance in a dynamic environment in the presence of sensor noise.

2. Develop the architecture of a UAV obstacle avoidance system.

3. Investigate methods for predicting future UAV coordinates and checking for collision risks.

4. Implement a trajectory correction algorithm that ensures safe avoidance while minimizing deviation from the route and controlling the energy cost of the maneuver.

5. Conduct a comparative study with common basic UAV motion control methods on standard trajectories using applied metrics and a generalized indicator of productivity.

Main Section

1. Construction of evasion trajectories based on path coordinates using RNN/LSTM for prediction

The proposed method implements a prediction-oriented evasion cycle of "prediction, risk assessment, trajectory correction," which is repeated at each discrete time step t. To generate the forecast, a window of the length of the previous measurements is used $(x_{t-n}, y_{t-n}) \dots (x_t, y_t)$, as well as current driving parameters v_t and θ_t and information about the nearest obstacles. The prediction horizon is determined by the number of steps N_p. Here *t* is the discrete time index (simulation step number), *n* This is the length of the input window (the number of previous trajectory points fed into the model).

Step 1 (input data preparation). The sequence of the last n trajectory points and the motion parameters are collected (v_t and θ_t) along with data on nearby obstacles.

Step 2 (coordinate prediction). The LSTM model generates the predicted coordinates of the UAV on the horizon *N_p*: $(\hat{x}_{t+1}, \hat{y}_{t+1}) \dots (\hat{x}_{t+N_p}\}, \hat{y}_{t+N_p})$.

Step 3 (collision risk check). The predicted trajectory is checked for intersections with the safety zones of obstacles within a radius of R. If an intersection is detected, potential points of conflict are identified.

Stage 4 (Trajectory Correction). If the risk of a collision is confirmed, a correction algorithm is activated, which generates an evasive maneuver that minimizes deviation from the route and controls energy consumption.

The UAV performs a corrected maneuver; in the next step t, the cycle repeats with updated sensor data.

1.1. Development of an architecture for a UAV obstacle avoidance system

In complex navigation scenarios where rapid and adaptive evasion is required, traditional methods may prove insufficient. The use of RNNs opens up new possibilities for predicting UAV trajectories by analyzing past coordinates and motion dynamics.

Unlike conventional methods, which calculate the trajectory based on current data, LSTM (Long Short-Term Memory) can take historical information into account and use it to predict the future position of the UAV. Thanks to its ability to remember significant events over long time intervals, LSTM is an ideal tool for motion prediction tasks.

The LSTM model consists of a cascade of memory blocks that filter the input data, removing insignificant information and retaining only important patterns. This allows the model to identify patterns in the UAV's motion and predict its coordinates with high accuracy.

When avoiding obstacles, the neural network receives the following input:

– a sequence of previous coordinates $(x_{t-n}, y_{t-n}) \dots (x_t, y_t)$;

–velocity and direction of motion;

–information about nearby obstacles.

The network generates predicted coordinates as output (x_{t+1}, y_{t+1}), which allows for determining the probability of a collision and adjusting the course before the UAV approaches an obstacle.

A block diagram of the proposed model is shown in Fig. 1.

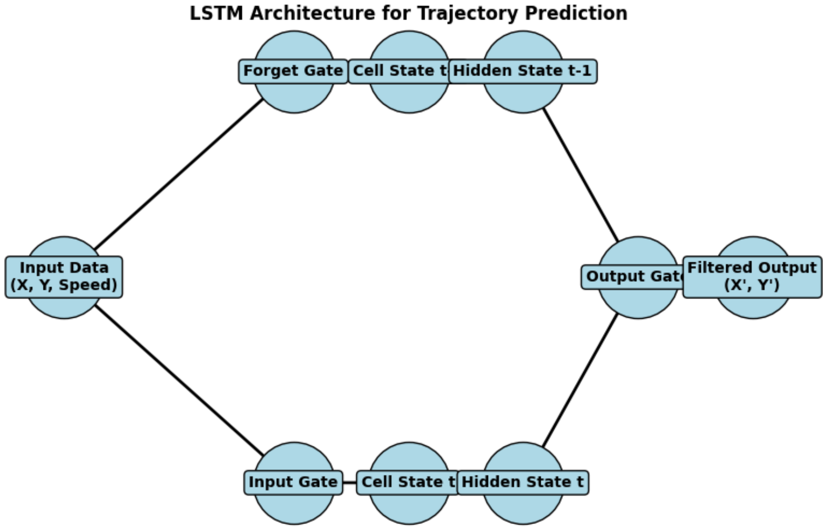

Fig. 1. Block diagram of an LSTM model for trajectory prediction

The main advantage of LSTM in forecasting tasks is its ability to account for nonlinear interactions in motion. This means that such a model can learn to adjust its trajectory even when obstacles appear unexpectedly or change their position.

In addition to directly predicting future coordinates, RNN/LSTM can be used to optimize evasion maneuvers by determining the safest and most energy-efficient route. For example, if a standard evasion algorithm suggests a sharp maneuver that could lead to energy loss, the neural network can adapt the maneuver to ensure an optimal balance between safety and flight efficiency.

Thanks to these advantages, the use of RNN/LSTM in UAV navigation systems allows for the simultaneous resolution of several important tasks:

–reducing delays in the evasion process – the network predicts hazards in advance, minimizing the risk of delayed reactions;

–adaptation to environmental changes – the system can respond to new threats without having to recalculate the route from scratch;

–motion optimization – smooth evasion is ensured, which minimizes deviation from the mission and saves energy.

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Thus, the use of LSTM in obstacle avoidance not only enhances flight safety but also ensures efficient, flexible, and intelligent UAV trajectory control.

Specifying the model shown in Fig. 1, it can be noted that the architecture of the UAV evasion system is based on a deep neural network that analyzes the environment, predicts potential threats, and generates an optimal maneuvering trajectory. The foundation of the architecture is the sensory perception module, which receives information about the space in front of the UAV, taking into account data from GPS, inertial measurement units (IMUs), lidars, and optical cameras. The sensor module transmits input data to the preprocessing subsystem, which performs noise filtering and measurement delay compensation. For this task, the study employs an LSTM, which allows for the recognition of temporal dependencies and the elimination of measurement drift.

The next component of the architecture is the UAV trajectory prediction module, which performs multi-step prediction of future coordinates based on time sequences of navigation data. The module receives the last n coordinate $(x_{t-n}, y_{t-n}) \dots (x_t, y_t)$ measurements, as well as motion parameters (v_t і θ_t) and information about nearby obstacles. The prediction module is implemented using a recurrent neural network with an LSTM architecture, which allows for the consideration of temporal dependencies and reduces the impact of sensor noise when estimating the future position of the UAV.

Next, the collision risk assessment module is executed: the predicted trajectory is compared with a map of obstacles (static or those that change configuration over time), taking into account the safety zone radius R. If the predicted trajectory crosses safety zones, potential conflict points are identified and a motion correction is initiated.

The trajectory correction module generates a corrective maneuver to ensure safe avoidance of the obstacle with minimal deviation from the initial route and with control over the maneuver's energy expenditure. The final element is the feedback module, which updates the forecast and decisions at every step based on new sensor measurements, ensuring continuous real-time trajectory adaptation.

The final component of the architecture is the feedback module, which provides deviation correction based on continuous monitoring of flight parameters. The use of recurrent neural networks in this module reduces prediction errors through adaptive real-time updating of the deviation model. This enables the UAV to adjust its behavior in response to dynamic environmental changes, avoiding sudden obstacles or changes in the trajectories of other objects.

The overall architecture of the evasion system combines modern methods of deep learning, recurrent forecasting, and real-time motion optimization. The interaction between its modules ensures high evasion accuracy, rapid response to threats, and flight stability even under challenging conditions.

Fig. 2 shows a block diagram of the UAV obstacle avoidance system architecture.

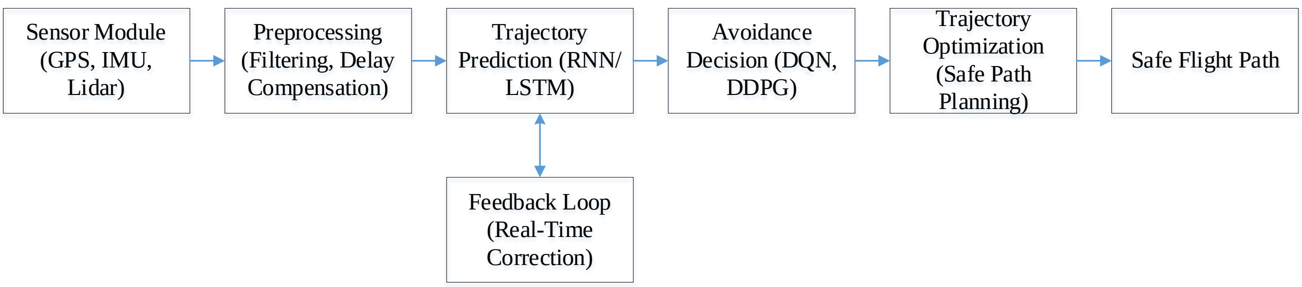

Fig. 2. Block diagram of the UAV obstacle avoidance system architecture

1.2. A method for predicting the future coordinates of a UAV

To ensure autonomous obstacle avoidance, a UAV must be able to predict its future position, taking into account its previous coordinates, speed, surrounding objects, and possible changes in flight conditions. The use of recurrent neural networks, specifically LSTMs, allows for the analysis of temporal dependencies in the flight path and the determination of predicted coordinates.

The basis of the prediction is the formation of an input data sequence used to train the neural network. The following are passed as input parameters to the *LSTM*: historical UAV coordinates $(x_{t-n}, y_{t-n}), \dots, (x_t, y_t)$,

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that reflect the device's previous position; speed and direction of movement v_t, θ_t, which enable the assessment of flight inertial characteristics; sensor data on surrounding objects that may affect course changes.

The task of the neural network is to construct a prediction function that estimates future coordinates (x_{t+1}, y_{t+1}) based on previous data:

$$(x_{t+1},y_{t+1})=f_\theta((x_{t-n},y_{t-n}),\dots,(x_t,y_t),v_t,\theta_t)$$

where f_θ– This is a function parameterized by the neural network's weights, which are optimized during training.

An important consideration is selecting the optimal prediction horizon. If the prediction horizon is too short, evasive maneuvers may be too late, increasing the risk of collision. On the other hand, an overly long horizon can lead to increased prediction error. The optimal value depends on the UAV's speed, the flight environment, and dynamic changes in obstacles.

The LSTM network is trained to minimize the loss function:

$$L = \frac{1}{N}\sum_{i=1}^{N}((x_{t+1}^{(i)} - \hat{x}_{t+1}^{(i)})^2 + (y_{t+1}^{(i)} - \hat{y}_{t+1}^{(i)})^2), \quad (1)$$

where L – the value of the loss function (*loss*), which is minimized during the training of an LSTM/RNN model; N – the number of training examples in the sample (or in the batch, if the computation is performed using a mini-batch); $x_{t+1}^{(i)}, y_{t+1}^{(i)}$ – the true (target) coordinates of the UAV in the next step, for example i; $\hat{x}_{t+1}^{(i)}, \hat{y}_{t+1}^{(i)}$ – the coordinates specified by the model for the next step, for example i.

This helps reduce the root mean square error of the forecast.

By using a neural network, the evasion system is able to anticipate a potential collision in advance, rather than merely reacting to the current situation.

Selecting the prediction horizon is a critical task, since a horizon that is too short may not allow enough time for maneuvering, while a horizon that is too long may increase the prediction error and lead to instability in the evasion system.

Optimal forecasting horizon T_p is defined as a trade-off between forecast accuracy, system response time, and maneuverability. Formally, the choice of the forecasting horizon can be described as an optimization problem that minimizes the sum of the forecast error and the collision risk.

Let us formalize the task of determining the forecasting horizon and consider it as an optimization problem.

The forecasting horizon determines how far ahead the LSTM network must predict the future coordinates of the UAV. Let us denote it as T_p, and the sampling interval as Δt. In that case, the prediction horizon in seconds is defined as: $T_p=N_p\cdot \Delta t$ of predicted points in the time series.

When selecting the optimal N_p, the following must be taken into account:

Forecast error. The forecast error increases with N_p, since the LSTM model operates in a recurrent mode and accumulates errors

$$e(N_p) = \frac{1}{N}\sum_{i=1}^{N} ((x_{t+N_p}^{(i)} - \hat{x}_{t+N_p}^{(i)})^2 + (y_{t+N_p}^{(i)} - \hat{y}_{t+N_p}^{(i)})^2), \quad (2)$$

the larger N_p is, the greater the error $e(N_p)$ becomes, which can render the forecast unreliable.

It should be noted that a UAV maneuver requires time to change its trajectory. This, in turn, depends on the aircraft's dynamic characteristics. The minimum required forecast horizon is determined by the formula:

$$T_{maneuver} = \frac{\Delta\theta}{\omega}, \quad (3)$$

where $\Delta\theta$ – a necessary change in the orientation angle; ω – UAV turn speed.

The probability of a collision $P_{collision}$ depends on the predicted trajectory of the UAV and surrounding objects. The safe prediction horizon must be sufficiently large to avoid obstacles:

$$P_{collision}(Tp) = \int_S p(x,y)\cdot\delta(x - x_{t+Tp}, y - y_{t+Tp})dxdy, \quad (4)$$

where $p(x,y)$ – the probability of obstacles appearing in a given area; $\delta(x - x_{t+Tp}, y - y_{t+Tp})$ – a UAV position marker that mathematically selects a point (xt,yt) $x - x_{t+Tp}, y - y_{t+Tp}$ in space.

The final optimization problem in the process of predicting the future coordinates of the UAV is defined as:

$$T_p^* = arg(\alpha e(N_p) + \beta P_{collision}(T_p) - \gamma T_{maneuver}), \quad (5)$$

where α, β, γ – weighting factors that determine the balance between prediction accuracy, collision risk, and maneuverability.

Depending on flight conditions, the prediction horizon can adapt dynamically. If the trajectory is stable (no sudden changes in direction, low probability of collision), the prediction horizon is extended to allow for more forward-looking avoidance.

$$T_p = min\,(T_p + \Delta T,\ T_{max}).$$

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If the predicted trajectory indicates a high risk of collision, the prediction horizon is shortened so that the evasion model can adapt more quickly to changes.

$$T_p = max\,(T_p - \Delta T,\ T_{min})$$

where T_{max}, T_{min} – boundary values of the forecast horizon.

1.3. Method for checking the possibility of collision

As shown in Fig. 2, after predicting the UAV's coordinates, it is necessary to assess the possibility of collisions with obstacles in the surrounding space. To do this, a map of the surrounding environment is constructed based on data from LiDAR, cameras, radars, and other sensors. The map can be represented discretely as a three-dimensional grid or as a continuous function describing the location of objects.

Based on this data, the next step involves assessing the collision risk. This assessment is based on comparing the predicted coordinates of the UAV with the spatial locations of static and dynamic objects. If the predicted trajectory (x_{t+1}, y_{t+1}) intersects an area occupied by an obstacle, the system determines the collision probability $P_{collision}$:

$$P_{collision} = \int_S p(x,y)\cdot\delta(x-x_{t+1}, y-y_{t+1})dxdy, \qquad (6)$$

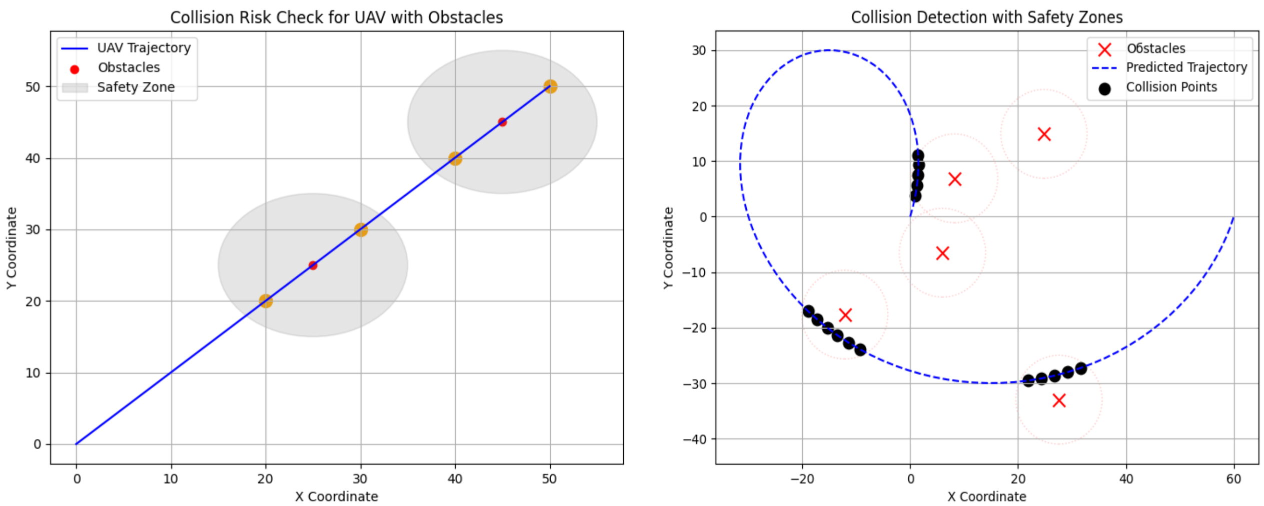
where $p(x,y)$ – probability distribution of the presence of an obstacle; $\delta(x,y)$ – a function that determines the UAV's position.

To ensure safety, a safety zone is defined around the device. This zone defines the area into which no obstacles should enter and can be represented as an ellipsoidal or spherical zone:

$$(x-x_t)^2+(y-y_t)^2 \le R^2, \qquad (7)$$

where R – safety zone radius.

Fig. 3 (a, b) shows illustrations of the results of implementing the presented method for checking for potential collisions.



a) b)

Fig. 3. Results of the collision detection method simulation

As can be seen in Fig. 3, the model generates random obstacles and displays them on the map. Obstacles can be static or dynamic objects. A safety zone is depicted around each obstacle, which likely defines the area that the UAV must not enter.

Next, the UAV's planned trajectory is generated, and the intersections of the future route with obstacles are checked using the safety zone. If an obstacle is detected, potential collision points with the obstacle are identified. If there is no risk of collision, the UAV's flight path remains unchanged. If the path passes too close to an obstacle, the model monitors the possibility of a collision and marks potential collision points on the diagram.

In Fig. 3, you can see the points where the UAV's path intersects the safety zones of the obstacles. These points are marked as "collision risk." This indicates that the program has successfully detected potential collisions and marked them on the diagram.

If the predicted coordinates go beyond the safety zone, the evasion mechanism is activated.

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1.4. Trajectory Correction Algorithm

When the system detects a collision threat, a new motion vector must be generated to ensure a safe evasion. To do this, the direction of motion is adjusted to avoid the obstacle without deviating significantly from the main route.

The trajectory correction task is formalized as an optimization problem:

$$Q^* = \underset{Q'(\cdot)}{argmin} \int_t^{t+\tau} (\| r(Q'(s)) - r_{goal} \|_2 + \lambda \| r(Q'(s)) - r_0(s) \|_2) ds, \qquad (8)$$

where Q' – new direction of movement; $r(Q'(s)$ – current trajectory; r_{goal} – initial route; $r_0(s)$ – reference (initial) trajectory at the moment s; λ – a weighting factor that balances the approach to the target with the minimum deviation from the reference route.

Course correction without losing the main heading is achieved using a parameter λ that determines the balance between collision avoidance and maintaining the optimal path.

The final choice of evasion maneuver depends on current conditions:

If the obstacle is stationary, the system can perform a smooth maneuver to fly around it. If the obstacle is moving, dynamic trajectory prediction is used to select the optimal moment for evasion. If there is no safe path, the system activates emergency braking and hovers in place.

Thanks to this approach, the evasion algorithm ensures continuous real-time trajectory adaptation and minimizes deviations from the mission.

The conducted modeling and research of the developed model allowed for the formation of a set of resulting data. Among them, Fig. 4 stands out, which presents the results of modeling the UAV's obstacle avoidance process using trajectory prediction and energy consumption reduction.

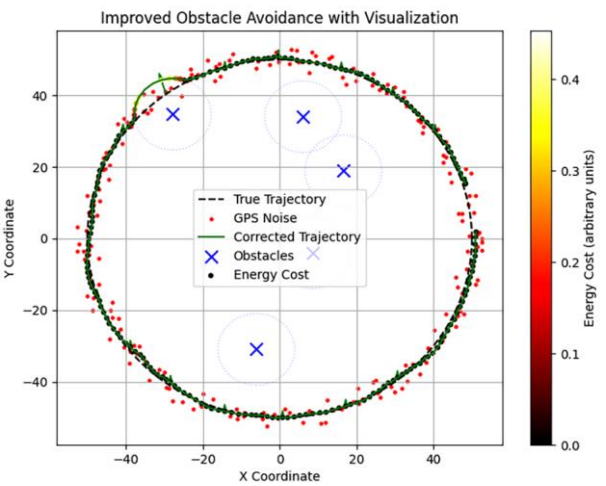

Fig. 4. Results of modeling the UAV obstacle avoidance process using trajectory prediction

The figure illustrates key navigation elements, including the actual trajectory, noisy GPS coordinates, the corrected trajectory after applying a neural network, as well as the location of obstacles and the energy costs of avoidance.

In Fig. 4, the actual trajectory line (indicated by a black dashed line) represents the ideal UAV flight path without accounting for noise, obstacles, or other external influences. It takes the form of a uniform circle, indicating stable flight along predefined coordinates.

GPS measurements (marked by red dots) exhibit random deviations from the true trajectory within ±3 meters, which corresponds to typical GPS errors under real-world conditions. They demonstrate significant fluctuations and deviations, which can complicate safe flight.

The corrected trajectory line (green line) shows the results of the proposed correction algorithm. It is obtained by predicting future coordinates using an LSTM recurrent neural network. Thanks to this, the model smooths out GPS errors and corrects the UAV's movement in response to detected threats.

The blue "x" markers indicate static obstacles located within the operational space. They are used to verify the effectiveness of evasion and to simulate collision scenarios. Each obstacle has a safety zone with a radius of 10 meters (safe_distance = 10) around it. If the UAV enters this zone, the evasion algorithm is activated.

Additionally, Fig. 4 illustrates the evasion directions (green arrows). They show the change in the UAV's trajectory in response to obstacle detection. The correction occurs in the direction that minimizes the risk of collision, while simultaneously accounting for energy expenditure.

Additionally, the colored dots on the corrected trajectory in the figure represent the energy expenditure required for evasion. The brighter the color (from yellow to dark red), the higher the energy expenditure. As shown in the figure, maximum energy expenditure occurs in areas of sharp maneuvering near obstacles.

As shown in Fig. 4, the use of a recurrent neural network allowed for significant smoothing of GPS noise distortions and the attainment of a more stable trajectory.

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The evasion algorithm adjusts the route in risk zones, ensuring safe navigation around obstacles.

Data on energy consumption in the proposed example are presented in Table 1.

Within the framework of simulation modeling, energy consumption is evaluated not as battery consumption, but as a conditional indicator of "maneuvering effort," which directly depends on the intensity of changes in direction of motion. At each step *t*, the course is calculated based on the sequence of coordinates:

$$\theta_t = atan2(y_t - y_{t-1}, x_t - x_{t-1}).$$

In that case, the instantaneous maneuvering "energy loss" is defined as the absolute change in heading:

$$e_t = |wrap(\theta_t - \theta_{t-1})|,$$

where $wrap(\cdot)$ reduces the angle difference to an interval $(-\pi; \pi]$. Total costs along a trajectory segment $E_{total} = \Sigma\, e_t$, are mean: $E_{mean} = (1/N)\, \Sigma\, e_t$, maximum: $E_{max} = max\, e_t$. Values e_t are used for color-coding points on the corrected trajectory (Fig. 4), while Table 1 contains aggregated metrics derived directly from the simulation data.

Table 1. *Summary data on energy consumption in the proposed example*

Total energy consumption (units)	Mean energy consumption (units)	Максимальні витрати енергії (у.о.)
2.3569	0.2143	0.3486

These results demonstrate the effectiveness of the proposed trajectory correction method using LSTM and adaptive obstacle avoidance.

1.5. Practical Application Example and Integration Option into an Autopilot

Let's consider a typical industrial scenario. Inspection of linear infrastructure (power lines/pipelines) or monitoring of a construction site, where the UAV flies along a specified trajectory and must avoid local obstacles (pylons, structures, equipment, temporary objects). Under such conditions, the evasion system receives:

– navigation estimates of position and motion parameters (coordinates, speed, heading) from GPS/IMU;

– information about nearby obstacles in the form of coordinates or distances to the nearest objects, obtained from onboard avoidance sensors or an external surveillance module.

The proposed method is used as a guidance-level add-on to the standard flight stabilization loop. At each step, a window of the last *n* navigation points and motion parameters is formed, an LSTM forecast of coordinates at horizon N_p is performed, after which the intersection of the predicted trajectory with safety zones of radius *R* is checked. If a risk is detected, a trajectory correction is generated, while the autopilot ensures stabilization and command execution.

The practical implementation within the scope of this article is presented as a software prototype in the Python environment (simulation modeling), which demonstrates the full loop of prediction, risk checking, and correction. Field testing is not within the scope of this work and is defined as the next validation stage, taking into account hardware limitations, sensor update rates, and real-time requirements.

We will conduct comparative studies of the developed UAV trajectory and deviation prediction for industrial autonomous missions in a dynamic environment and evaluate its effectiveness.

2. Comparative studies of the proposed method for predicting UAV trajectory and deviation

To evaluate the effectiveness of the developed method and determine its practical value, this article conducts comparative studies of the proposed method for predicting UAV trajectories and deviations against existing methods [30–32]. The following research strategy is proposed for this purpose.

Comparisons were made between methods similar in purpose. These methods are:

− Pure Pursuit;

− Line of Sight;

− Vector Field;

− Nonlinear Stabilization;

− Intelligent control with prediction based on RNN/LSTM.

Performance evaluation was carried out using criteria that highlight the practical advantages (and disadvantages) of our development. The main parameters used for comparison are:

− average deviation from the trajectory (meters);

− adaptation time after deviation (seconds);

− number of obstacle avoidance maneuvers;

− minimum distance to an obstacle (meters);

− average energy consumption (conditional units);

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− trajectory tracking success rate (%) (ratio of the distance traveled without exceeding the permissible deviation to the total distance);

− overall productivity coefficient.

To obtain the necessary data, simulation modeling was performed using Python and the required libraries numpy, scipy, and pandas.

The developed simulation model allowed for testing algorithms on standard trajectories (straight line, circle, polyline) and collecting the corresponding statistical data. The results of the simulation modeling are presented in Fig. 5–11 and in Table.

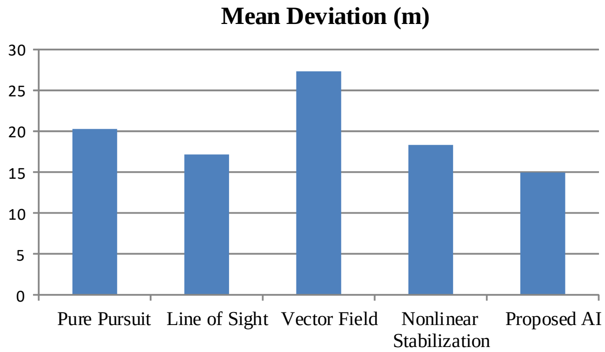

Fig. 5. Results of a comparative study of the “Proposed AI” method based on the “average deviation from the trajectory” metric

First, trajectory tracking accuracy was examined (see Fig. 5). The average deviation indicates the extent to which each method enables the UAV to maintain route stability. In this regard, the Proposed AI method proved to be the most effective, demonstrating the smallest deviation (14.95 m). This indicates the algorithm’s ability to quickly correct the trajectory and maintain flight stability. In contrast, the Vector Field method had the largest deviation (27.32 m), indicating the instability of this approach.

Another important factor is the adaptation speed after deviation, which assesses how quickly the UAV returns to the optimal trajectory (see Fig. 6). The Line of Sight and Nonlinear Stabilization methods demonstrated relatively short adaptation times of 26–30 seconds. The Proposed AI method, although it took 39 seconds to stabilize, compensated for this with flight accuracy and overall efficiency. The Vector Field method had the longest delay (47 seconds), which negatively affects its application in complex conditions.

Significant attention was paid to safety issues, namely obstacle avoidance and minimum distance to objects (see Fig. 7).

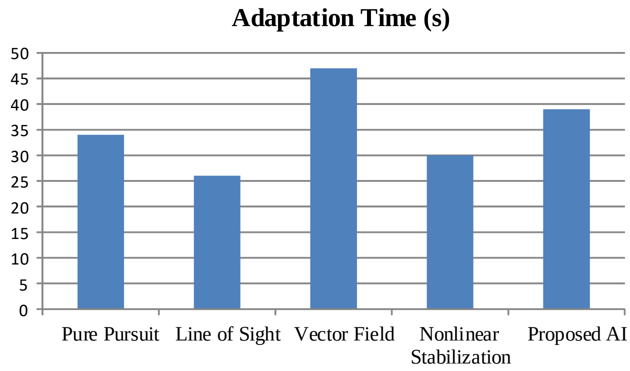

Fig. 6. Results of a comparative study of the “Proposed AI” method based on the “adaptation time after deviation (seconds)” metric

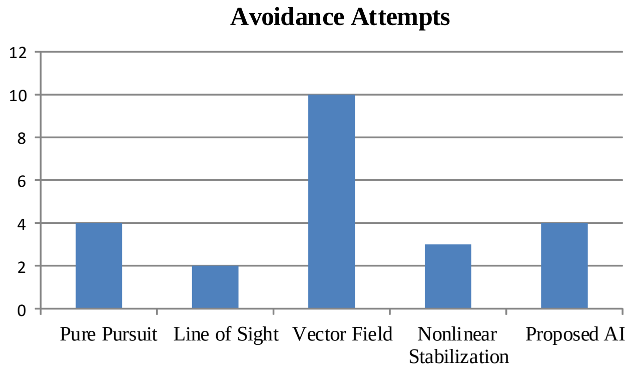

Fig. 7. Results of a comparative study of the “Proposed AI” method based on the “number of obstacle avoidance maneuvers” metric

The number of obstacle avoidance attempts indicates how frequently the algorithm detects a hazard and adjusts its course. In this regard, Vector Field had the highest number of attempts (10), indicating trajectory instability and potential erroneous maneuvers. In contrast, Proposed AI had only 4 attempts, demonstrating a balance between evasion and the minimization of unnecessary corrections.

The minimum distance to obstacles is another important criterion (see Fig. 8). In this regard, the Nonlinear Stabilization method (7.66 m) provided the highest level of safety, while Vector Field (5.81 m) demonstrated a risk of collisions. The Proposed AI method (6.12 m) fell within the optimal balance between evasion efficiency and stability maintenance.

Energy consumption also plays a significant role in selecting a UAV control method (see Fig. 9).

The maneuver energy consumption index E_{total} was calculated identically for all methods using the formulas given above, on the same standard trajectories (straight line, circle, polygon), and under identical

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simulation parameters. Thus, the comparison in Fig. 9 reflects the relative "cost of maneuvering" of different algorithms under common experimental conditions.

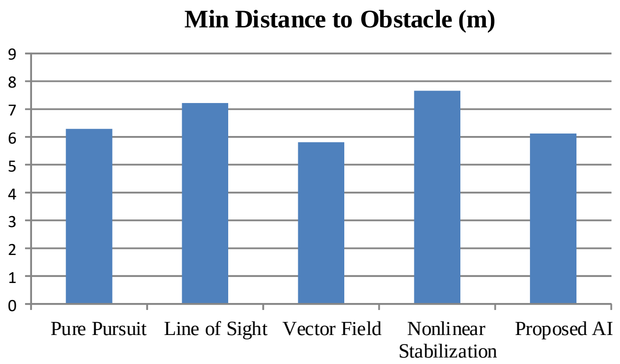

Fig. 8. Results of a comparative study of the "Proposed AI" method based on the "minimum distance to obstacle (meters)" metric

The Proposed AI (72 conventional units) proved to be the most economical, allowing for an increase in autonomous flight duration. By comparison, Vector Field (135 units) consumed the most energy, indicating its inefficiency for use in long-duration missions.

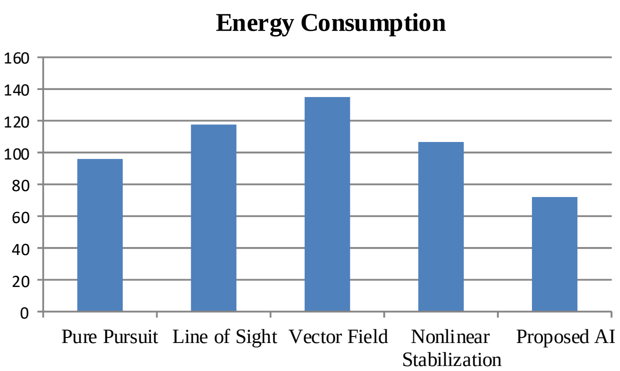

Fig. 9. Results of a comparative study of the "Proposed AI" method based on the "total maneuvering energy consumption" metric

An important factor is trajectory tracking performance, which reflects the percentage of the distance traveled without exceeding the permissible deviation (Fig. 10). In this regard, Proposed AI (86.08%) again demonstrated the best result among all methods. This indicates that the algorithm most effectively keeps the UAV within permissible motion parameters, which is a key factor for application in autonomous missions. The Nonlinear Stabilization (82.84%) and Line of Sight (84.31%) methods also performed well, while Vector Field (73.66%) lagged significantly, indicating trajectory instability and a higher probability of errors.

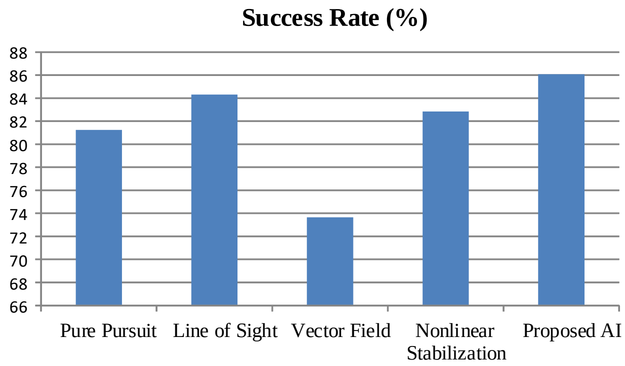

Fig. 10. Results of a comparative study of the "Proposed AI" method based on the "trajectory tracking success" metric

The final criterion of effectiveness is the overall productivity index (OPE), which combines all the aforementioned metrics (see Fig. 11). In this regard, Proposed AI achieved the best value (0.494), which is the highest among all the methods considered. This is 10% better than "Pure Pursuit," 5% better than "Line of Sight," 18% better than "Vector Field," and 8% better than "Nonlinear Stabilization." This demonstrates the comprehensive effectiveness of the method, which combines accuracy, adaptation speed, energy efficiency, and safety.

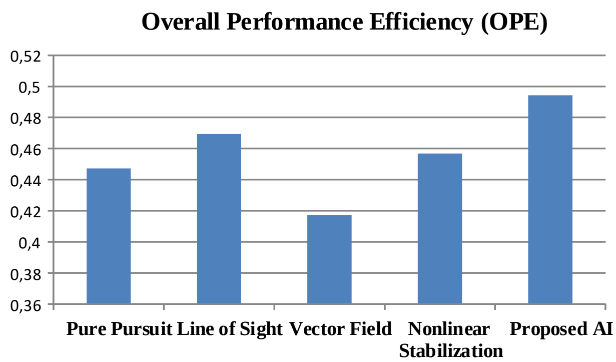

Fig. 11. Results of a comparative study of the "Proposed AI" method based on the "trajectory tracking success" metric

Thus, within the scope of the conducted simulation-based comparative study on standard trajectories and using selected evaluation metrics, the proposed method (Proposed AI) demonstrates the best overall performance (in particular, based on the generalized OPE metric) among the approaches considered, combining tracking accuracy, energy efficiency, and an acceptable level of evasion safety. The obtained results confirm the feasibility of using a prediction-oriented evasion scheme; field validation on real UAV platforms is considered a direction for further research.

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Conclusions

In this article, within the framework of simulation modeling, the current scientific problem of developing a method for predicting UAV trajectories and evasion for industrial autonomous missions in a dynamic environment under conditions of noisy navigation measurements is solved. The method uses time series of coordinates and motion parameters for multi-step prediction of the UAV's position, which makes it possible to detect potentially dangerous approaches **before** entering the risk zone and avoid delayed reactions characteristic of purely reactive approaches.

An architecture for a UAV obstacle avoidance system has been developed, comprising modules for sensor data acquisition and preprocessing, prediction of future coordinates based on LSTM, collision risk assessment through formalization of the safety zone, and trajectory correction. This structure provides a coordinated "prediction, risk assessment, motion correction" loop.

A method for predicting future coordinates and checking for collision risks has been investigated. Conflict checking is performed by analyzing the intersection of the predicted trajectory with obstacle safety zones; if a threat is detected, potential risk points are identified, which initiates the evasion procedure. Additionally, the selection of the prediction horizon is considered as a key parameter that determines the balance between lead time and the accumulation of prediction error, with the possibility of adapting it depending on traffic conditions.

A trajectory correction algorithm has been implemented that ensures safe evasion while minimizing deviation from the route and controlling the energy costs of the maneuver. A simulation example demonstrates how the corrected trajectory is formed, and evasion maneuvers are performed in risk areas with the energy costs displayed on the trajectory.

A comparative study of the proposed method was conducted against common basic UAV motion control methods on standard trajectories using performance metrics and a generalized coefficient of productivity. According to the comparison results, the proposed method demonstrated the smallest average deviation from the trajectory **14.95 m**, the lowest average energy consumption **72 u.o.**, the highest tracking success rate **86.08%**, as well as the highest value of the integral indicator **OPE = 0.494** among the approaches considered. At the same time, it was shown that trade-offs are possible for individual metrics: in particular, the minimum distance to the obstacle for the proposed method is **6.12 m**, whereas the maximum minimum distance in the experiment was achieved by the Nonlinear Stabilization method (**7.66 m**), which highlights the difference in priorities between methods and the importance of a comprehensive evaluation based on multiple criteria.

Promising directions for further research include extending the scenarios to cases with more pronounced obstacle dynamics, transitioning to a full three-dimensional framework accounting for altitude and altitude gain/loss constraints, and validation using experimental data or field tests. In particular, we plan to conduct field validation on a DJI Mavic-class UAV in a typical industrial scenario, measuring decision-making delays in real time and safety metrics. Separately, we will evaluate the computational budget of the LSTM module in inference mode and apply model optimization for on-board or companion computing.

Conflict of interest

The authors declare that they have no conflicts of interest, including financial, personal, authorial, or any other nature, that could influence the research or the results published in this article.

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Data availability

Data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies to write this paper.

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МЕТОД ПРОГНОЗУВАННЯ ТРАЄКТОРІЙ ТА УХИЛЕННЯ БПЛА ДЛЯ ПРОМИСЛОВИХ АВТОНОМНИХ МІСІЙ У ДИНАМІЧНОМУ СЕРЕДОВИЩІ

Розглянуто задачу прогнозування траєкторії та випереджувального ухилення безпілотного літального апарата у промислових автономних місіях у динамічному середовищі за наявності шуму навігаційних вимірювань і обмежень енергоресурсу, що зумовлює ризики запізнілого або надмірного маневрування та зростання відхилення від маршруту. **Мета**. Розробити та верифікувати на імітаційній моделі метод, який забезпечує прогнозно-орієнтоване ухилення від перешкод із контролем відхилення від опорної траєкторії та маневрових енерговитрат. **Завдання**. Сформувати архітектуру системи ухилення; розробити прогнозатор майбутніх координат на основі рекурентної нейронної мережі з довготривалою короткочасною пам’яттю; визначити спосіб перевірки ризику зіткнення із використанням зони безпеки; реалізувати алгоритм корекції траєкторії з урахуванням компромісу «безпека–відхилення–енерговитрати»; виконати порівняльне оцінювання з базовими методами. **Методи**. Прогноз координат будується за часовими послідовностями координат і параметрів руху; ризик зіткнення оцінюється шляхом аналізу перетину прогнозованої траєкторії із зонами безпеки перешкод; корекція траєкторії формалізується як оптимізаційний вибір маневру, що мінімізує сумарну похибку слідування та штраф за зближення. Ефективність перевірено у середовищі Python на стандартних траєкторіях (пряма, коло, ламана) з порівнянням із методами чистого переслідування, лінії візування, векторних полів і нелінійної стабілізації. **Результати**. Запропонований підхід забезпечив найменше середнє відхилення від траєкторії 14,95 м, найнижчі маневрові енерговитрати 72 умовні одиниці, найвищу успішність слідування 86,08 % та найбільший узагальнений коефіцієнт продуктивності 0,494 серед розглянутих алгоритмів; зафіксовано компроміс за мінімальною дистанцією до перешкод. **Висновки**. Метод прогнозно-орієнтованого ухилення підвищує інтегральну ефективність навігації у моделях промислових місій; подальші дослідження передбачають натурну валідацію на реальних платформах та оптимізацію обчислювальних витрат прогнозатора.

Ключові слова: безпілотний літальний апарат; промислові автономні місії; прогнозування траєкторій; уникнення перешкод; рекурентна нейронна мережа; корекція траєкторії; енергоефективність.

Бібліографічні описи / Bibliographic descriptions

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