Method of local UAV navigation using neural networks⋆

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Abstract
This paper reviews algorithms for UAV navigation and stabilization. The advantages and disadvantages of known algorithms are identified and a method for local UAV navigation using convolutional neural networks (CNN) and recurrent neural networks (RNN) is proposed. A deep convolutional neural network (CNN) in combination with a recurrent network (LSTM) is used to estimate the distance to objects and form a map of the environment. The input data consists of a sequence of video frames processed by CNN to extract features, and then transferred to LSTM to calculate spatial changes. As a result of the study, it was found that the proposed local navigation method based on CNN-LSTM-SLAM neural networks provides significantly higher accuracy of drone positioning in space than traditional methods. In particular, the average absolute error MAE for this method was 0.15 m, which is significantly less than that of optical flow (0.32 m) and IMU method (0.45 m). This demonstrates the ability of the neural network approach to more accurately predict drone movements.

Keywords
UAV, navigation, neural networks, CNN, LSTM, SLAM

1. Introduction

Unmanned aerial vehicles (UAVs), known as drones, have become an integral part of the modern world, finding application in various spheres of human activity. Their popularity is due to their versatility, accessibility and ability to perform tasks that were previously unattainable or required significant resources.

One of the most common areas of use of drones is aerial photography and videography. Due to the ability to climb to considerable heights and maneuver in confined spaces, drones allow you to obtain unique footage used in the cinematography, journalism and advertising industries.

In addition, they are actively used in agriculture to monitor crops, detect pests and optimize irrigation and fertilizer processes, which increases the efficiency of agricultural production.

In the military sphere, drones have made a real revolution, changing the tactics of warfare. They are used for reconnaissance, adjusting artillery fire, delivering cargo and even as strike weapons. In particular, during the war in Ukraine, drones became an important tool for gaining an asymmetric advantage over the enemy, allowing for effective targeting and minimizing risks to personnel.

However, to ensure the safe and efficient operation of drones, it is necessary to implement reliable stabilization mechanisms. Flight stability is critical for performing precise maneuvers, obtaining high-quality images and preventing emergency situations. Without proper stabilization, the drone

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can become uncontrollable, which will lead to potentially dangerous consequences, especially in urban environments or during critical missions.

Drone stabilization ensures their ability to withstand external influences, such as wind gusts, turbulence or sudden changes in load. This is especially important when performing tasks in extreme conditions or when operating at high altitudes. Reliable stabilization systems allow the drone to maintain a given trajectory and orientation, which is necessary for the accurate execution of missions and ensuring the safety of both the operator and others around it.

In addition, modern drones often rely on global navigation satellite systems (GNSS), such as GPS, to determine their location and navigation. However, in conditions where the GNSS signal may be unavailable or intentionally suppressed, there is a need to develop autonomous navigation algorithms that do not depend on external signal sources. Such algorithms will allow drones to effectively perform their tasks even in difficult conditions, ensuring high accuracy and reliability of navigation.

Drones open up wide opportunities in various industries, but their effective and safe use is impossible without the implementation of modern stabilization mechanisms and autonomous navigation systems. The development and improvement of such technologies is a key direction in the development of unmanned aerial vehicles, which will contribute to the expansion of their application and increase the reliability of performing the tasks assigned. Therefore, the use of neural networks to improve local UAV navigation is a relevant and important task today.

2. Overview of existing drone navigation and stabilization algorithms

In modern unmanned aerial vehicles (UAVs), navigation and stabilization are interrelated processes that ensure accuracy, safety, and flight efficiency. These functions are implemented through the integration of various algorithms, sensor systems, and control technologies that work together to maintain the stability and controllability of the drone under various external influences.

2.1. Navigation algorithms

Traditionally, drones have used GPS to determine their location. However, in environments with limited or no GPS signal, alternative methods are used. One key approach is simultaneous localization and mapping (SLAM) algorithms, which allow a drone to build a map of an unknown environment and determine its position relative to that map using data from cameras, lidar, and inertial measurement units. This is especially important for navigating indoors or in urban environments where GPS signals may be unavailable or distorted.

Thus, in [1] an end-to-end UAV simulation platform for SLAM, navigation research, and applications was introduced, including the detailed simulator setup and an out-of-box localization, mapping, and navigation system. In [2] the authors propose a novel and complete framework to realize the autonomous landing of UAVs in unknown indoor scenes based on visual SLAM, semantic segmentation, terrain estimation, and a decision-making model. The paper [3] describes an application of the Cartographer graph SLAM stack as a pose sensor in a UAV feedback control loop, with certain application-specific changes in the SLAM stack such as smoothing of the optimized pose. The article [4] presents a survey of simultaneous localization and mapping (SLAM) and data fusion techniques for object detection and environmental scene perception in unmanned aerial vehicles (UAVs).

Another approach is to use star navigation, where the drone navigates by the location of stars in the night sky. This method is particularly useful in cases where GPS is unavailable or jammed. Scientists have developed algorithms that can determine the location of the drone from a series of images of the night sky with an accuracy of up to four kilometers, even in difficult conditions, such as the presence of wind. Algorithms such as A* and Dijkstra's algorithm are widely used for flight path planning, which calculate the shortest path to the target while avoiding obstacles. This ensures efficient and safe drone navigation in complex environments. For example, an extension of the A* algorithm, known as Cell A*, allows for stable route planning with less computational overhead, which is important for long-duration missions.

In [5] the evaluation function is revised by using dynamic weighting; use azimuth to change the search neighborhood, and adjust the search method adaptively according to different map areas; then, considering the influence of the actual size of the UAV, set the UAV and the safety radius of obstacles. The study [6] introduces an improved algorithm for three-dimensional path planning in obstacle-rich environments, such as urban and industrial areas. The proposed approach integrates the A* search algorithm with a customized heuristic function which incorporates local obstacle density. The study [7] proposes an efficient algorithm to detect air pollution in urban areas using UAVs. An improved A-star algorithm that can efficiently perform searches based on a probabilistic search model using a UAV is designed.

In cases where it is necessary to coordinate the movement of several drones at the same time, swarm intelligence and reinforcement learning algorithms are used. These methods allow a swarm of drones to effectively explore unknown territories, avoiding obstacles and coordinating their actions to achieve a common goal. In particular, Q-Learning algorithms help each drone in the swarm make optimal decisions based on its own experience and information from other drones.

Thus, in [8] the authors propose an adaptive conversion speed Q-Learning algorithm (ACSQL). Performing UAV missions autonomously is divided into two stages: rescue mission search stage and optimal path search stage. In [9] the authors develop a DRL framework for UAV autonomous navigation in a high dynamic and complex environment. The authors of [10] propose Q-learning algorithm to efficiently plan the path of UAVs in environments containing both static and dynamic obstacles. The study [11] proposes a new system that employs Q-Learning and ANNs with two dense layers to control UAV swarms in maps with obstacles.

2.2. Stabilization algorithms

One of the key components of mechanical stabilization is gyrostabilized camera gimbals. These gimbals use data from gyroscopes to compensate for unwanted movements and vibrations, providing a stable image during flight. There are two- and three-axis gimbals, which allow you to compensate for the movements of the drone along the corresponding axes, ensuring smooth video recording and accurate navigation. Studies show that the combination of mechanical stabilization with digital signal processing allows you to achieve high image quality even in conditions of significant vibrations and external disturbances. At the software level, PID controllers (proportional-integral-derivative controllers) are widely used, which process data from inertial sensors to maintain a stable position of the drone. However, in complex and noisy environments, traditional PID controllers may not be effective enough. In such cases, advanced controllers such as Proportional-Integral-Derivative-Accelerated (PIDA) with genetic filters are implemented. These algorithms allow to improve the stability and accuracy of the drone flight, effectively compensating for the influence of external disturbances and noise.

Our previous study [12] was aimed at FPV drone stabilization on an automatically determined target and its further observation. The study [13] proposes video repeater design concept for UAV control.

Current research is aimed at implementing deep learning algorithms for automatic adjustment of stabilization parameters. In particular, the use of deep learning methods with reinforcement, such as Proximal Policy Optimization (PPO), allows the drone to adaptively adjust its control parameters in real time, ensuring optimal stability and maneuverability even in dynamically changing conditions.

Thus, despite the significant development of navigation and stabilization algorithms, there is a need to create new methods that will ensure the autonomous operation of unmanned aerial vehicles without dependence on external signals, such as GPS. This study is aimed at developing a method for drone navigation and stabilization that will use a camera to determine the position in space and adjust the flight. Modern approaches, such as computer vision, SLAM algorithms and swarm intelligence, demonstrate effectiveness in complex environments, but they have limitations in processing speed, energy consumption and adaptability to unpredictable conditions. The proposed method will allow the drone to autonomously navigate in space, which is critically important for operation in environments with obstacles or under the influence of electronic warfare. The use of real-time image analysis algorithms will ensure stable maintenance of the device in a given position and accurate navigation, which opens up new opportunities for its application in military, rescue and research missions. Further development in this area should be aimed at creating localized algorithms capable of operating effectively in GPS-failure environments, ensuring the stability and accuracy of drone flight in critical conditions.

3. Local navigation method

Local navigation of an unmanned aerial vehicle (UAV) is a complex task that requires the integration of computer vision, sensor analysis, and machine learning methods. The absence of GPS or other global positioning systems makes it difficult to determine the location of the drone, which requires the use of autonomous navigation methods. The main idea of the method is to use convolutional neural networks (CNN) and recurrent neural networks (RNN) to analyze the video stream and calculate the relative position of the drone in space. The neural network allows you to obtain the necessary characteristics of the environment, which are critically important for building a flight trajectory.

Let $I_t(x, y)$, image obtained from the drone camera at time t, $P_t(x_t, y_t, z_t)$ - its coordinates in space. The task of local navigation is to determine the trajectory P_{t+1}, which ensures flight stability and obstacle avoidance. This uses a comprehensive approach that includes image segmentation, object detection, and scene depth analysis.

3.1. Model architecture

A deep convolutional neural network (CNN) combined with a recurrent network (LSTM) is used to estimate the distance to objects and form a map of the environment. The input data consists of a sequence of video frames, processed by the CNN to extract features, and then passed to the LSTM to calculate spatial changes.

Formally, each frame I_t turns into signs F_t using a convolutional network can be denoted by the Formula 1.

$$F_t = CNN(I_t), \tag{1}$$

where F_t is feature vector obtained after image processing I_t a convolutional neural network that extracts structural and textural information about the environment.

The recurrent layer uses the features described in the Formula 2 to predict position changes.

$$\Delta P_t = LSTM\left(F_t, F_{t-1,\dots,}F_{t-n}\right), \tag{2}$$

where ΔP_t is a vector of change in the drone's position, estimated based on the analysis of previous features $F_t, F_{t-1,\dots,}F_{t-n}$ etc., using the long-term memory mechanism to detect patterns in the motion.

The new position vector is calculated by the Formula 3.

$$\hat{P}_{t+1} = P_t + \Delta P_t, \tag{3}$$

where $\hat{P}_{t+1}$ are predicted coordinates of the drone at a given point in time $t + 1$, which are determined based on the current situation P_t and displacement ΔP_t.

3.2. Route correction

The resulting coordinates are used to update the local map and avoid obstacles. This is done using the simultaneous localization and mapping (SLAM) method, where each frame is compared with the previous ones, and key points of the image are stored in the local map and denoted by the equation 4.

$$M_t = \mathrm{SLAM}(L, P_t), \tag{4}$$

where M_t is a current map of the environment containing information about the location of objects relative to the drone.

Route correction is performed using gradient descent, which minimizes the error between the desired and actual trajectory (Formula 5).

$$P_{t+1} = P_t - \eta \frac{dL}{dP_t} \tag{5}$$

where η is a learning speed, L is a loss function that determines the deviation from the desired trajectory.

3.3. Neural network training algorithm

The neural network is trained in two stages: pre-training in safe conditions on a simulator and further refinement of the model in real operating conditions. First, a simulator is used to generate a data set that includes various flight conditions, obstacles and variable environmental parameters. The network is trained to minimize the error between the predicted and actual coordinates (Formula 6).

$$L = \sum_{t=1}^{T} \left\| P_t - \hat{P}_t \right\|^2, \tag{6}$$

where L is the loss function that measures the difference between the true position of the drone P_t and predicted $\hat{P}_t$.

Optimization is carried out using the gradient descent method denoted by the Formula 7.

$$\theta_{t+1} = \theta_t - \eta \frac{dL}{d\theta}, \tag{7}$$

where θ denotes model parameters, η is a learning rate. After completing simulation training, the model is transferred to real conditions, where it adapts based on data obtained from the real environment.

Auxiliary sensors are used to improve local navigation accuracy. Barometer estimates altitude h_t, which is included in the drone state vector (Formula 8).

$$S_t = (F_t, h, C_t), \tag{8}$$

where C_t is the orientation of the drone, obtained from the compass, and F_t is a feature vector from the camera. Taking these parameters into account allows to increase the resistance to external interference.

Based on the obtained coordinates and the landmark map, the drone velocity vector is determined, which is controlled via a PID controller and denoted by the Formula 9.

$$V_{t+1} = K_p(P_{t+1} - P_t) + K_d\left(\dot{P}_{t+1} - \dot{P}_t\right) + K_i \sum_{i=1}^{t} (P_i - P_{i-1}), \tag{9}$$

where K_p,K_d,K_i is PID controller coefficients that control the proportional, differential and integral contributions to the drone's speed according to the position error. This controller allows you to maintain stable movement even in difficult conditions.

The proposed method combines computer vision, deep neural networks and sensor data to provide autonomous local drone navigation. The use of CNN and LSTM allows you to predict the change in position in space, and the integration of additional sensors increases the accuracy and reliability of the system. The PID controller ensures stability of movement based on the calculated coordinates. This approach can be used for autonomous systems operating in GPS-unavailable conditions, ensuring high navigation efficiency even in dynamic scenarios.

4. Experiments and Results

To evaluate the effectiveness of the proposed method, an experimental study was conducted, including a comparison with other local navigation methods. The main goal of the experiments was to determine the navigation accuracy, processing speed, and resistance to interference in different conditions.

4.1. Conditions for conducting the experiment

The study was conducted in a test environment that included simulation of real-world flight conditions using a simulator and physical experiments with a real drone. Three main scenarios were identified:

- Stable environment. Minimal distractions, well-lit room.
- Changing environment. Presence of dynamic objects (moving obstacles).
- Low light. Testing operation in conditions of limited visibility.

Each navigation method was tested in all three environments to evaluate its performance. Three methods were selected for comparison: the proposed CNN-LSTM-SLAM, an optical flow-based method, and a method using only IMU data.

4.2. Evaluation metrics

The results were analyzed according to the following indicators, which allow us to evaluate the accuracy, adaptability and efficiency of the proposed method.

The first criterion was the mean absolute error (MAE) in determining the location of the drone. It was calculated by the Formula 10.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |P_i - P_i^*|, \tag{10}$$

where P_i is an actual drone position, P_i^* is the predicted position, N is the number of test points.

The second indicator was the resistance to environmental changes, which was assessed by the percentage of correctly adjusted trajectories when new objects appeared.

The last criterion was the processing time required to analyze one frame and calculate the correction commands.

4.3. Experiment results

As a result of the experiments conducted, Table 1 was obtained.

The table shows that the proposed CNN-LSTM-SLAM method provides significantly better positioning accuracy (MAE = 0.15 m) compared to optical flow (MAE = 0.32 m) and IMU method

(MAE = 0.45 m). Although the CNN-LSTM-SLAM method has a slightly longer processing time (35 ms), this is compensated by high noise immunity (94%), which is superior to traditional methods. Additionally, testing was carried out in real conditions with strong wind and precipitation. However, the results of this experiment were not taken into account in the overall analysis due to the impossibility of repeating the weather conditions for each method participating in the experiment. Despite this, observations showed that the proposed method demonstrates higher resistance to external factors compared to traditional navigation methods.

Table 1
Test results of three methods

Method	MAE (m)	Processing time (ms)	Resistance to interference (%)
CNN-LSTM-SLAM (proposed in this paper)	0.15	35	94
Optical flow	0.32	20	68
IMU-data	0.45	10	40

5. Conclusions

As a result of the study, it was found that the proposed method of local navigation based on neural networks CNN-LSTM-SLAM provides a significantly higher accuracy of drone positioning in space than traditional methods. In particular, the average absolute error MAE for this method was 0.15 m, which is significantly less than the optical flow (0.32 m) and the IMU method (0.45 m). This indicates the ability of the neural network approach to more accurately predict the movement of the drone.

In addition, the proposed method demonstrates high resistance to interference (94%), which is almost twice as high as the similar indicator for the IMU method (40%) and significantly better than in the case of optical flow (68%). This confirms the effectiveness of using CNN-LSTM in complex conditions with dynamic objects.

The only drawback of the method is a slightly longer frame processing time (35 ms), compared to other methods, such as IMU (10 ms) and optical flow (20 ms). However, this difference is justified in view of the obtained accuracy and stability.

Thus, the results of experimental studies confirmed the effectiveness of the proposed approach for autonomous drone navigation in GPS-unavailable conditions. It is a promising solution for application in complex dynamic environments, such as urban areas, forests or search and rescue operations.

Further research will be aimed at improving the data processing speed and reducing the computational complexity of the method. In particular, a promising direction of development is the optimization of the neural network architecture for operation on limited computing resources, which will allow implementing the system on less powerful drones. The possibility of integrating additional sensors, such as lidars and radar systems, to improve navigation accuracy in difficult weather conditions and in the absence of visual information will also be investigated.

Declaration on Generative AI

The author have not employed any Generative AI tools.

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