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USING A NEURAL NETWORK TO IMPROVE THE COURSE STABILITY OF UAV IN THE GNSS DENIED ENVIRONMENT

This paper is devoted to the development of a concept for improving the accuracy of keeping the course of airplane-type unmanned aerial vehicles in the absence of satellite navigation signals in conditions of unknown wind load using neural networks. The paper describes the results of the development and training of a neural network based on data collected during UAV training flights. The results of the work can be used to modify existing UAV flight controllers in order to improve the accuracy of their autonomous functioning in the conditions of electronic warfare.

Key words: *neural networks, data analysis, unmanned aerial vehicle, autonomous navigation system.*

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ВИКОРИСТАННЯ НЕЙРОННОЇ МЕРЕЖІ ДЛЯ ПІДВИЩЕННІ КУРСОВОЇ СТАБІЛЬНОСТІ БПЛА ЗА ВІДСУТНОСТІ GNSS

Робота присвячена розробці концепції підвищення точності утримання курсу безплоітних літальних апаратів літакового типу при відсутності сигналів супутникової навігації в умовах невідомого вітрового навантаження за допомогою нейронних мереж. В роботі описано результати розробки та навчання нейронної мережі на основі даних, зібраних під час навчальних польотів БПЛА. Результати роботи можна використати для модифікації існуючих польотних контролерів БПЛА з метою підвищення точності їх автономного функціонування в умовах дії засобі радіоелектронної боротьби.

Ключові слова: *нейронні мережі, аналіз даних, безпілотний літальний апарат, система автономної навігації.*

Introduction and problem statement. Unmanned aerial vehicles (UAVs) are currently used in many areas of modern life. The most relevant at the moment is the military sector. Reconnaissance and tactical surveillance of the enemy, use as radio-controlled munitions, delivery of payloads to places inaccessible for delivery by other means - this is an approximate list of military applications of UAVs. At the same time, in the face of enemy electronic warfare (EW), the effective use of UAVs becomes extremely difficult due to the inability to use signals from the satellite navigation system (GNSS). Especially dangerous is the so-called spoofing, in which GNSS signals are spoofed, causing the UAV's navigation system to receive incorrect coordinates and lead it in the wrong direction. Without satellite navigation signals, maintaining the correct course can be challenging for UAVs due to wind interference, which tends to push the UAV off course. Therefore, developing alternative navigation methods in the absence of GNSS signals is crucial.

Analysis of the latest research and publications. The issue of reliable navigation in the absence of GNSS can be solved by several methods. For example, a structural approach to dividing navigation tasks into subcomponents was proposed in [1]: Where is the controlled object? Where is it going? What routes can it take to get there? In addition to this, [2] made an exhaustive, detailed review of research on the subcomponents of environment perception, localization, and route planning. It was found that almost 62% of all studies were devoted to UAV location, while only 16% presented a fully implemented navigation system containing all of the above subcomponents. According to their analysis, it is expected that potential future research will utilize more efficient sensors. In particular, miniature radars, cameras recording changes, and sensors using external radio signals (e.g., signals from mobile towers, cell phones, etc.). All of this will necessarily be combined with new, more efficient algorithms, most often based on artificial intelligence methods.

It is also worth highlighting several review articles on computer vision-based navigation. In particular, [3] investigated a computer vision-based navigation system that can work both indoors and outdoors. The paper analyzes the limitations and advantages of the route planning and collision avoidance subcomponents. In [4], navigation strategies were divided into three groups: without using maps, using ready-made maps, and those that create maps during navigation. They also investigated the subcomponents of obstacle avoidance, localization and mapping, and route planning. Paper [5] provides an overview of another navigation system based on computer vision. It was found that the vast majority of implementations that combine mono and stereo cameras with an inertial measurement system (IMU) are faster, require less power and memory compared to implementations that use a system of simultaneous localization and mapping (SLAM). A group of researchers in [6] considered navigation methods using optical flow as one of the computer vision technologies. They identified and described the problems of quantifying environmental parameters and processing high-resolution images in real time.

Current trends in the research of autonomous navigation of unmanned aerial vehicles indicate a gradual increase in the share of artificial intelligence technologies [7], where the authors classified artificial intelligence-based navigation technologies into optimization-based approaches (e.g., ant and genetic algorithms) and learning-based approaches (e.g., deep learning).

Based on the analysis of the research, it can be assumed that further research will focus not only on improving existing concepts, but also on creating new big data processing systems using artificial intelligence against the background of large computing power and greater energy efficiency.

The aim of the study. To develop a concept for improving the accuracy of aircraft-type UAVs in GNSS-denied environments and in the face of wind loads of unknown direction and intensity, by combining onboard sensors with neural networks.

Experimental methodology. The main methodology of the experiment for this article is to develop a system of additional sensors on the UAV and collect data from them for further training of a neural network, the purpose of which will be to correct the course in the conditions of wind drift of the UAV. In more detail, the experimental methodology can be described as follows:

1. Installing additional sensors on an airplane-type UAV.
2. Setting up the UAV flight controller to collect data from additional sensors.
3. Collecting data from the sensors: performing UAV flights with course keeping by magnetometer in different directions and intensities of wind load.
4. Preparing the collected data for training the neural network.
5. Selection of the neural network architecture and its training.
6. Analysis of the results.

Presentation of the main research material. This article focuses on exploring the potential of neural networks to enhance the course-keeping accuracy of aircraft-type UAVs under the influence of wind with unknown intensity and direction. The UAV is equipped with an onboard magnetometer, which facilitates accurate orientation in the intended direction. However, the presence of lateral wind can cause deviations from the desired course, leading to a Return-To-Home (RTH) Error, as illustrated in Figure 1.

In this paper, we propose to use two additional airspeed sensors (Pitot tubes) (Fig. 2a) installed perpendicularly (Fig. 2b) to the longitudinal axis of the aircraft to analyze the UAV's heading error. To interpret the signals from them, a neural network pre-trained during training flights will be used.

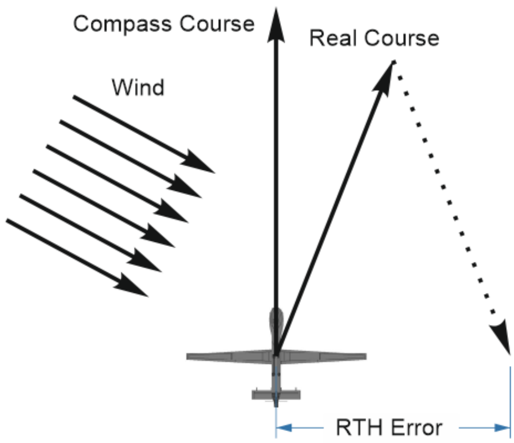
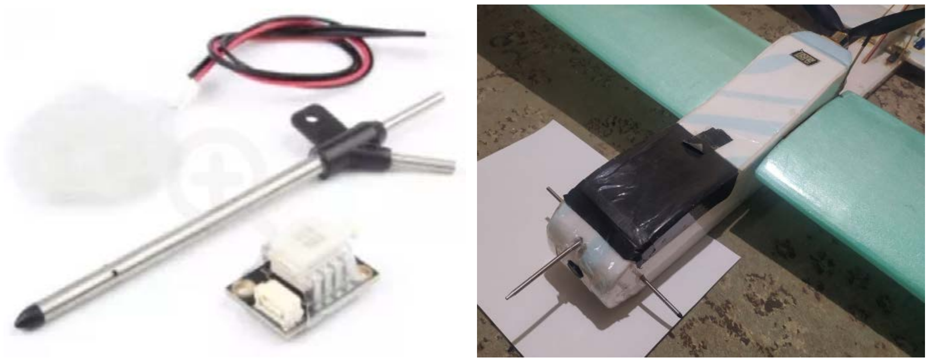


Fig. 1. **Illustration of the problem of drifting a UAV off a given course by a wind**

For the neural network, a classical full-connection architecture with two hidden layers of 100 and 50 neurons, respectively, was chosen. The following data were fed to the neural network:

- magnetometer course (Compass Course);
- data from three airspeed sensors;
- the position of the UAV's directional rudder.

The output of the neural network should be the value of the UAV's real course. During the training process, the output of the neural network was compared with the UAV heading value obtained using GNSS coordinates collected during training flights. As a result, the weights of the neural network links should be adjusted in such a way that it can then predict the correct course of the UAV based on airspeed sensors with sufficient accuracy without using the GNSS system.



a) b)

Fig. 2. **Installation of airspeed sensors**

a) airspeed sensor; b) placement of sensors on aircraft-type UAVs

A diagram of the neural network architecture is shown in Figure 3.

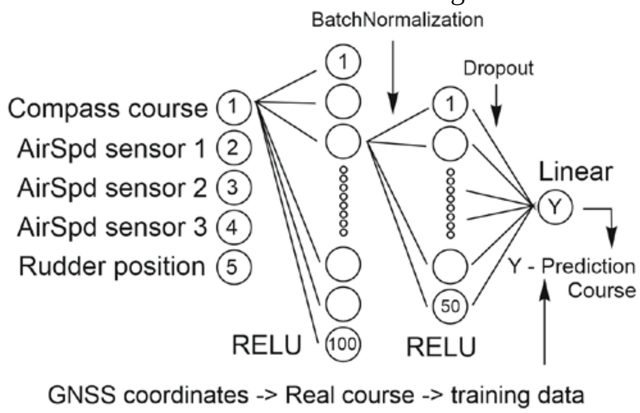


Fig. 3. **Architecture of the neural network**

The Python interpreter with the Keras framework was used to create and train the neural network. The RELU function was chosen as the activation function for the hidden layers, and a linear activation function was chosen for the output neuron, i.e., the weighted sum of the activations of the previous layer. To eliminate the overfitting process observed during training, Batch normalization and Dropout with standard parameters were applied.

The training dataset consisted of 40,000 samples collected during 12 flights lasting 60-80 minutes. Each sample contained: 1 magnetometer heading value, 3 values from airspeed sensors, 1 UAV directional rudder position value, and 2 geographic coordinates (longitude and latitude) from the GNSS receiver. The data were collected using a recorder built into the Matek H743 Wing flight controller with modified INAV 5.1 firmware.

After adjusting the neural network parameters, the error in calculating the UAV's real course was reduced to 19.2% after 50 epochs. The results are shown in the graph (Fig. 4).

Conclusions. The use of a neural network in combination with additional airspeed sensors allows predicting the real course of an aircraft-type UAV with an error of 19.2% in the face of wind drift of unknown direction and intensity.

Thus, it can be concluded that the proposed methodology is promising for improving the accuracy of autonomous operation without the use of global satellite navigation signals. Further work will focus on combining the developed neural network with a flight controller and testing the resulting navigation system in real-world conditions.

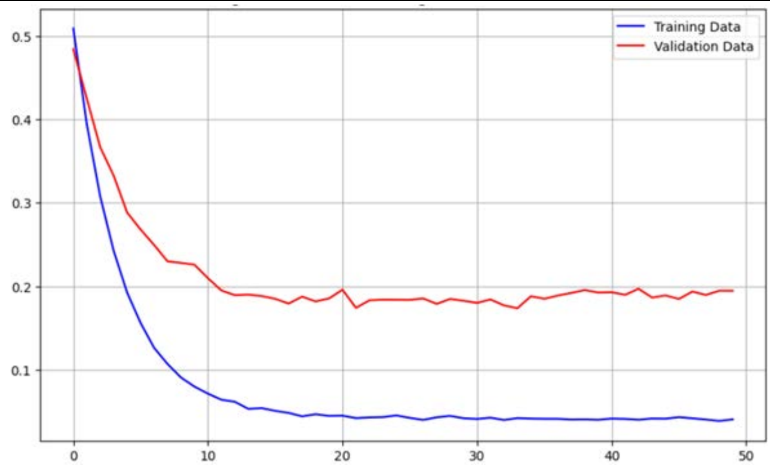


Fig. 4. **Results of neural network training**

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