UDC 629.7.014-519.072.1 **doi: 10.32620/reks.2023.1.12**

David NASO[1], Olha POHUDINA[2], Serhij YASHIN[2], Andrii POHUDIN[2], Rossella BARTOLO[1]

[1] ***Polytechnic University of Bari, Bari, Italy***
[2] ***National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine***

AUTONOMOUS FLIGHT INSURANCE METHOD OF UNMANNED AERIAL VEHICLES PAROT MAMBO USING SEMANTIC SEGMENTATION DATA

Autonomous navigation of unmanned aerial vehicles (UAVs) has become in the past decade an extremely attracting topic, also due to the increasing availability of affordable equipment and open-source control and processing software environments. This demand has also raised a strong interest in developing accessible experimental platforms to train engineering students in the rapidly evolving area of autonomous navigation. In this paper, we describe a platform based on low-cost off-the-shelf hardware that takes advantage of the Matlab/Simulink programming environment to tackle most of the problems related to UAV autonomous navigation. More specifically, the subject of this paper is the autonomous control of the flight of a small UAV, which must explore and patrol an indoor unknown environment. Objectives: to analyse the existing hardware platforms for autonomous flight indoors, choose a flight exploration scenario of unknown premises, to formalize the procedure for obtaining a model of knowledge for semantic classification of premises, to formalize obtaining distance to obstacles using data camera horizontally employment and building on its barrier map. Namely, we use the method of image segmentation based on the brightness threshold, a method of training the semantic segmentation network, and computer algorithms in probabilistic robotics for mobile robots. We consider both the case of navigation guided by structural visual information placed in the environment, e.g., contrast markers for flight (such as path marked by a red tape), and the case of navigation based on unstructured information such as recognizable objects or human gestures. Basing on preliminary tests, the most suitable method for autonomous in-door navigation is by using\ object classification and segmentation, so that the UAV gradually analyses the surrounding objects in the room and makes decisions on path planning. The result of our investigation is a method that is suitable to allow the autonomous flight of a UAV with a frontal video camera. Conclusions. The scientific novelty of the obtained results is as follows: we have improved the method of autonomous flight of small UAVs by using the semantic network model and determining the purpose of flight only at a given altitude to minimize the computational costs of limited autopilot capabilities for low-cost small UAV models. The results of our study can be further extended by means of a campaign of experiments in different environments.

Keywords: *unmanned aerial vehicles; convolutional neural network; semantic segmentation; flight control system; occupancy grid.*

Introduction

Autonomous systems that belong to the field of artificial intelligence applications will become increasingly important for technical system developers in the future. The tasks of interaction on heterogeneous platforms of autonomous technical systems are among the priority areas of investment in many countries. Such technical complexes find various applications, for example, for filming territories affected by military conflicts, natural disasters, or places difficult to access for patrolling.

In this paper we develop platform to perform tasks such as: monitoring of various areas, inspection of basements, and dungeons, reconnaissance with semi-autonomous navigation. Having the capability to autonomously plan, reconfigure, and perform tasks for an unmanned aerial vehicle (UAV) is a crucial component of UAVs group, enabling the exploration of large, complex, and unknown environments, like in these competitions [1]. Also, it is important to develop innovation effectively and to provide solutions to the problems that matter to roboticists and society. It becomes necessary to have development platforms that facilitate the acquisition of basic competences and skills for programming video processing methods using low-cost small UAV models.

The research is targeted at the choosing a way of structuring visual information for the autonomous flight of a low-cost small UAV; then simulate and perform a test flight over a given area indoors with the construction of a map of the detected obstacles. The object of the study is the monitoring of indoor processes using video information obtained by an autonomous UAV. The subject of the research is the methods and means of processing video information received from a UAV video camera, using semantic data segmentation technologies.

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

Structurally, the information is presented as follows: in the first section, the existing hardware platforms for autonomous flight was analysed. In the second section, the methods of structuring visual information was analysed, and in the third section, the strategies and choice of a flight research scenario in unknown spaces was analysed. In the fourth section, the developed method and results in the form of constructed barrier maps was presented. To develop a method of autonomous UAV flight based on video camera data, the semantic segmentation network learning method, computer algorithms in probabilistic robotics for mobile robots were used.

1. Analysis of existing hardware platforms and scenarios for autonomous indoor flight

UAV autonomous operation modelling is practiced on micromodels, among which the most popular are: PARROT Mambo model, DJI Tello EDU, DJI ROBOMASTER TT, and Bitcraze Crazyflie. The hardware platform of such UAVs allows for autonomous flight indoors. To work with these UAV models are provided: a software development kit for Parrot Copters [2]; Tello SDK 2.0 [3]; ROBOMASTER TT SDK 3.0 [4]; open libraries for copter Crazyflie [5]. Well-known programming environment MATLAB contains packages to simulate these UAVs [6, 7]. DJI UAVs models have more limitations when planning an autonomous flight since the control systems are closed for modifications, and very popular tools such as the Bitcraze Crazyflie UAV model cannot be reprogrammed with high-level languages. Therefore, the PARROT model was chosen for further consideration. MATLAB platform and built-in UAV PARROT tool has a high degree of connectivity [8], and integrated simulation based on hardware allows you to perform a quick and realistic test of both aircraft and flight scheduling algorithms.

When performing tasks with autonomous UAVs, it is important to determine the purpose of the flight to set algorithms for the behavior of the UAV in real time, considering the characteristics of the environment and of the tasks to be executed. It is also necessary to implement some form of accelerated task planning, in case of perturbations, or changes in environmental conditions. Three types of tool kits have been applied in such scenarios: localization, mapping, and planning. The localization kit uses onboard sensor information, such as that provided by a stereo camera [8, 9]. The used architecture gives an accurate localization result (error < 0.3 m). It allows you to obtain a cloud of points, which can later be used in the system for fly planning. But this subsystem is not available for low-cost small UAV [10]. To solve such problems, the analysis of visual information coming from cameras installed on board UAVs is often used [11]. In studies [9, 11], localization is carried out in conjunction with flight planning. Here, the flight must occur in a prepared room where the specified markers are located, usually of a contrasting colour. In work [9], a visual toolkit was proposed for flight planning. This is important for teaching visual navigation techniques on inexpensive UAV models. In [10] are proposed collision-free path planner based on the rapidly exploring random trees variant, for safe and optimal navigation of robots in 3D spaces. When developing an alternative that works only on camera video data, it is necessary to compare the results with such models.

Theoretical research on this problem is aimed at developing methods for structuring visual information [11, 12] and its transformation into data and commands to change the behavior of UAVs. When implementing these methods in the practice of UAV flights, it is important to process the input data: eliminate noise in the obtained images, consider external flight factors (wind, lighting), and consider hardware errors.

2. Methods for structuring visual information of UAV PARROT

Smart UAV technologies include two main areas of research. The first area includes the development of intelligent flight controllers and path planning methods. The second area focuses on applying deep learning techniques to extract useful information from sensory data collected by the drone [13]. For autonomous UAVs, these areas of study are often considered together because after extracting useful information (for example, from a video), it is necessary to make real-time decisions (e.g., path or task planning) based on such data.

One very straightforward option is to use computer vision has the main or unique source of information, and perform autonomous navigation accordingly [14, 15]. This is also the scenario investigated in this paper. For example, consider the movement of a UAV over a curved line drawn on the floor. The proposed model consists of two parts (fig.1): analysis of video stream image data and operation of the control system. In this task, it is important to recognize a line that is in contrast with other flooring elements [16]. In case of corners appearing, it is necessary to change the yaw angle, and in case there is no line on the video stream image, the UAV must find the landing marker (circle) and land.

Reference [17] suggests deep learning as a tool to develop a vision-based UAVs Pursuit-Evasion. A deep convolutional neural network (CNN) is used to detect objects of interest (UAV) and estimate the necessary controls for the follower UAV to keep the target UAV within its field of view and the closest possible to the centre of the image frame.

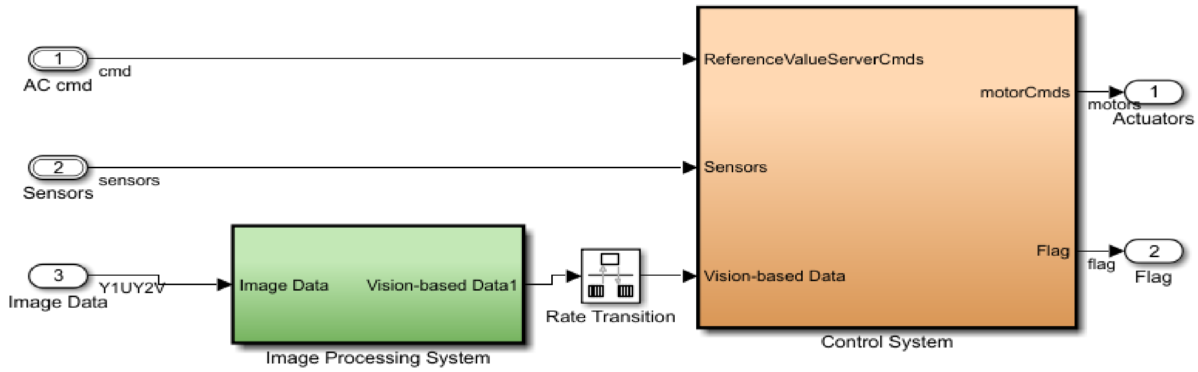


Fig. 1. Flight Control System

YOLO v2 was used as the UAV detector since it was the best performing in complex outdoor conditions and faster enough to enable the processing at a rate of 30fps for a real-time tracking of the UAV. Deep learning and CNN are also used to train agents that control mini UAVs based on hand gestures in [18].

Following the example of implementing semantic segmentation for terrestrial autonomous vehicles [19], this method of extracting data from video is used to control the movement of UAVs [20, 21]. The work [22] provides a link for applying a trained semantic network for UAV, which is used outside. The main semantic segmentation algorithms which are used for UAV video data are: grayscale image processing, conditional random field, and deep learning. The datasets for image segmentation are used as input data for setting up the semantic segmentation system and subsequent decision making about the flight plan based on video data. After training the system, it is necessary to check the correctness of its operation. The most popular metrics are Pixel Accuracy, Mean Pixel Accuracy (mPA), Intersection over Union (IoU), Jaccard index, Dice index, and F1-score [23].

The practical result of this work is the creation of an obstacle avoidance system for UAVs using only a monocular camera (available in low-cost small UAVs). In [22] used the feature point detector Speeded Up Robust Features for fast processing of obstacles, on unknown positions. Extended StixelWorld [20] used colour information to learn the model's obstacles. Deep neural network models have recently demonstrated remarkable performance improvements shown to outperform most traditional methods. Also, vision-based methods have poor performance under extreme illumination conditions such as shadows and direct sunlight.

The choice of the UAV visual information structuring method significantly affects the amount of data received, and therefore the speed of obtaining it. Accordingly, an autonomous UAV control system will be algorithmically connected to the visual information processing subsystem.

3. Scenarios of autonomous flight of UAV PARROT using visual data

Consider the scenarios that are used by UAVs for autonomous flight, considering visual information indoors:

− patrolling the environment. In this scenario, the dimensions of the environment are known in advance. Based on the data on the size of the premises and the technical capabilities of the UAV, the route (snake, chaotic, etc.), landing conditions are selected. Visual information can be transmitted during the flight or analysed after landing. In the Parrot Mambo model, it is possible to monitor from the lower camera, originally built into the UAV body, but it is intended for navigation. For live broadcasting, an additional camera equipped with a transmitter is used. Reviews indicated that in the case of Mambo PARROTS, the transmitted image lags behind the actual camera view [2];

− recognition and observation of the object (fig. 2). Here, an object must be known in advance, which can be stationary (for example, a line drawn on the floor) or moving (for example, people or another UAV). Preliminary training or adjustment of the video information processing subsystem for this object is required. During the flight, the UAV analyses the features of a given object in the focus of the camera, after recognition, as a rule, its location is estimated and algorithms for changing the coordinates, speeds, or angles of the UAV flight are performed;

− exploration of an initially unknown area indoors (fig. 3). In such a case, it is necessary to have semantic information from a deep learning model. Based on these data, a virtual map is created during the flight. Since we assume that the PARROT UAV flies at a certain altitude, and due to the limited computing capabilities of the video information processing subsystems and the control system, we assume that the mapping will be restricted to 2D maps.

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

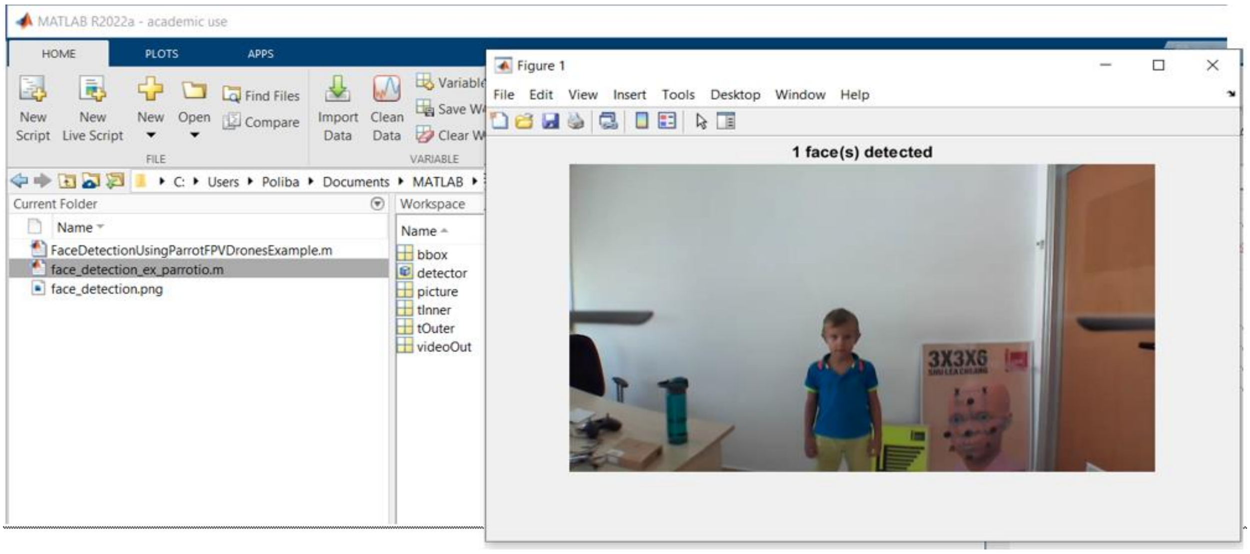
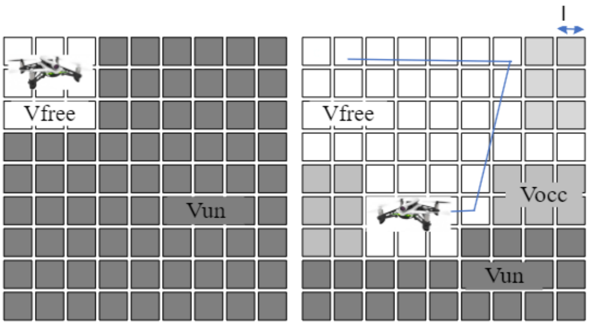


Fig. 2. Recognition and observation of the object



a) start fly b) fly around the territory

Fig. 3. Virtual 2D map

The map consists of minimal square blocks (block side length l). The choice of block size is related to the UAV movement algorithm. Fig. 3 shows an example of how the system works. The map contains free Vfree, occupied Vocc and unknown Vun areas for flights.

4. The method of exploration of an initially unknown area indoors

The PARROT UAVs are equipped with a FPV camera that provides images measuring 640x360 pixels. The image data are used to develop vision-based algorithms. Therefore, the image data obtained from the FPV camera is a 360-by-640-by-3 matrix of type uint8, in RGB format.

For simulation purposes, it is important to define how to represent the camera «Field of View» (FOV). The camera will be attached at the centre of UAV recording toward its X-Axis body frame. To be able to represent the camera FOV, we will need the following camera specifications:

– depth of view D, which represents the maximum distance the camera can clearly record D=2 m;

– the angle in which the camera lens can record ($\Theta = 110°$).

These parameters give an approximate coverage of the considered area of 1 m × 2 m. To prepare the data and the autonomous flight algorithm, the UAV made a test with video recording. The resulting video was processed in the subsystem pixelLabelTraningData (c). As a result, data were obtained (“Image datastore” and “Pixel label datastore”) for training the semantic segmentation network (the function trainNetwork was used).

The resulting semantic segmentation network (SSN) will be used to automate the flight with the following conditions:

– the flight will be made above the floor,

– when recognizing furniture objects, it is necessary to estimate the distance to them, for subsequent placement on a virtual map.

The next important task is to determine the distance to the detected furniture objects. To calculate the distance, you should know the internal and external parameters of the camera. The internal parameters of the camera can be found using the calibration procedure in (Single Camera Calibrator App) and the external parameters:

– the height of its placement above the floor (UAV flight height – h, fig. 4),

– tilt angle (depends on the pitch angle).

To find the distance to the object on the segmented frame, the coordinates of the rectangular area (bbox) describing the UAV are found, and the coordinates of the point t1 are calculated, and then, using the coordinate transformation, the coordinates of the point t1 are calculated in the “top view” coordinate system [24]. In the new system, the x coordinate is the distance to the opposite object (L).

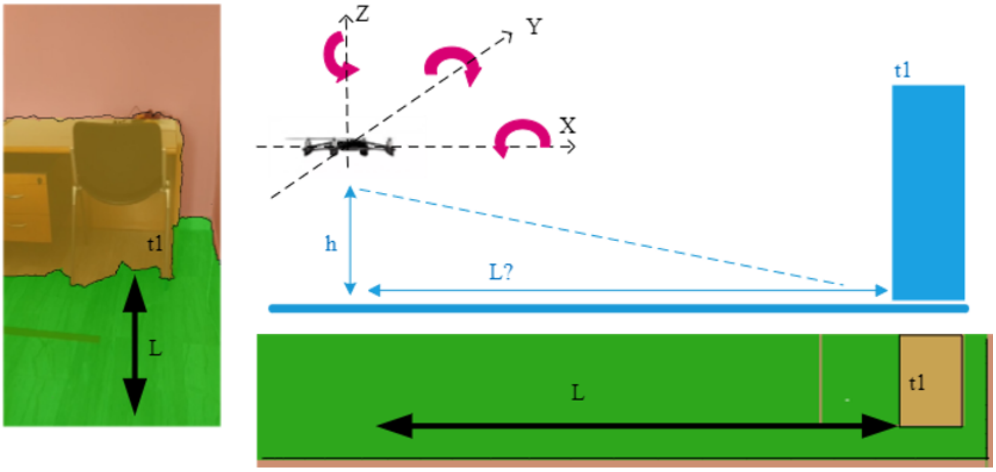


Fig. 4. Determining the distance to obstacles

The resulting trained SSN model and determining the distance to obstacles method are used in the UAV flight algorithm.

The method consists of the following steps:

1. The virtual space matrix Occupancy grid is initialized. The UAV is taking off, and the cell in which the UAV is taking off is considered the Vfree area, and the rest are Vun.

2. The UAV makes a 360° turn, after which 4 image data corresponding to 0°, 90°, 180°, 270° are processed. In each image, the number of pixels corresponding to the "floor" category is calculated. The results were ranked and recorded in the priority direction matrix.

3. If UAV movement direction, with the highest priority belongs to the Vfree category:

3.1. The UAV turns to an appropriate angle.

3.2. The distance L to the obstacle is estimated.

3.3. Cells that are at a distance L are fixed as Vocc.

3.4. The UAV flies the distance L/2 and stops, each flight cell is fixed as Vfree in the matrix Occupancy grid; then step 2 is performed (fig. 5).

Else: if the directions of movement are not completed: the next priority is chosen, else the completion of the UAV flight.

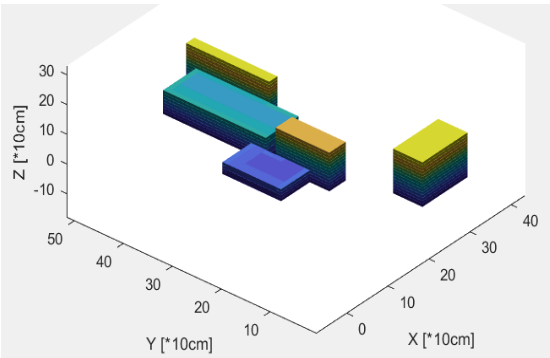


Fig. 5. Occupancy grid

The occupancy grid is a grid of values, each of which indicates an obstacle in a specified area. Values can be binary (0 for empty cells, 1 for cells occupied by an obstacle) or take values in a given range, indicating the possibility of the specified area.

On fig. 5, the height of the obstacles is set randomly. Thus, the map considers a room 4×5 m with 5 obstacles, which are pieces of furniture.

The quality of the proposed method depends on the algorithm of semantic segmentation, which is used at the second stage. The standard measure used to evaluate the performance of semantic segmentation's algorithms is the IoU. Given an image, the IoU measure gives the similarity between the predicted region and the ground-truth region for an object present in the image, and is defined as the size of the intersection divided by the union of the two regions [23]:

$$IoU_c = TP_c/(TP_c + FP_c + FN_c),$$

where TP_c, FP_c, FN_c denote the number of true-positive, false-positive, and false-negative pixels, respectively for class c. After evaluating the recognition results of individual classes, we found the average IoU (Tabl. 1).

Table 1

IoU measure

IoU for class:	Result
floor	0.93
furniture objects	0.47
walls	0.88
windows	0.24
Averaged IoU	0.63

The video stream data received after the test flight was segmented. The segmentation results were compared with manual segmentation. A result IoU>0.5 is considered acceptable.

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

5. Discussion

Clearly, some limitations have to be considered, which include the battery autonomy (about 10 minutes) and the computational power onboard of the UAV. These limitations can be considered, however, also a means to challenge the creativity of the users. With regard to this aspect, this paper only presents some of the preliminary ideas and their margins for improvement. We have shown that the hardware is suitable for perform a phased flight of an unknown area based on the segmentation of the environment. Using it, as well as the method of obtaining the distance to objects-obstacles of the MATLAB library, we have successfully developed an algorithm for the autonomous flight of a small UAV. In the future, it is necessary to conduct a detailed campaign of experiments to assess the benefits and limitations of the semantic segmentation and develop more robust (less sensitive to parameter calibration) and adaptive autonomous planning and navigation algorithms.

The specific drawbacks that should be taken into account are mainly related to the sensing devices used, that is, the monocular camera has the drawback of the high sensitivity to lighting conditions; such as direct sun light may led to a lack of information.

Conclusions

The autonomous flight method of UAV Parot Mambo using semantic segmentation data for objects indoors is developed in the article.

The scientific novelty of the study lies in a was improved the method of autonomous flight of small UAVs by using the semantic network model and determining the purpose of flight only at a given altitude to minimize the computational costs of limited autopilot capabilities for low-cost small UAV models.

The study's practical significance lies in the fact that we design a model-based algorithm on Simulink and Matlab through simulation, and study how to test it by deploying on the Hardware of a Parrot Mambo Fly mini-drone through the interfaces provided with its Hardware support package in Simulink. We used the generated source code in real-time applications such as rapid prototyping, simulation, and hardware-in-the-loop tests with Simulink Coder.

During the test flight, the results of the semantic segmentation were displayed on the screen to assess the quality of the resulting neural network. In parallel, statistics were collected to calculate the IoU. Because of several flights, IoU=0.63 was obtained, which is an acceptable result for further application in UAV automatic flight algorithms.

Further research will be aimed at solving the problem of occupancy map construction accuracy and increasing UAV flight time. We are planning changes in the UAV hardware architecture because the coordinates of obstacles will also be obtained from additional devices: lidar, laser pointer. It will make it possible to specify the coordinates of both the UAV position and the position of surrounding objects. The software architecture will be changed too. For the final calculation of the coordinates provided by various sensors, the capabilities of the open packages ROS2 and the NAV2 tool will be used. The planned decision is to maintain the capability to hardware-in-loop testing of the actual flight control system. This will significantly speed up the developing of a flight control system.

Contributions of authors: formulation of the purpose and tasks of research, formulation of conclusions – **David Naso**; analysis of methods for structuring visual information – **Rossella Bartolo**; analysis of scenarios of autonomous flight – **Sergiy Yashin**; development of methods and analysis of research results – **Olha Pohudina**; evaluation of the quality of the semantic segmentation algorithm – **Andrii Pohudin.**

All authors have read and agreed to the published version of the manuscript.

Acknowledgement. The work was supported by the Ministry of Education and Science of Ukraine, and the state registration numbers of the projects are 0121U109605 and 0122U000860.

References

1. Agha, A., Otsu, K., Morrell, B., Fan, D.D., Thakker, R., Santamaria-Navarro, A., Kim, S.-K. et al. Quest for Robotic Autonomy in Challenging Environments; An Overview of TEAM CoSTAR's Solution at Phase I and II of DARPA Subterranean Challenge. *ArXiv,* 2021, pp.1-77. DOI: 10.48550/arXiv.2103.11470.

2. Parrot Software Development Kit RCS. *PARROT DRONES SAS PARIS,* 2021. 84 p. Available at: https://www.parrot.com/assets/s3fs-public/2022-01/whitepaperanafiai.pdf (accessed 27 June 2022).

3. Tello. SDK 2.0. *Ryze Tech Support*, 2018. 8 p. Available at: https://dl-cdn.ryzerobotics.com/downloads/Tello/Tello%20SDK%202.0%20User%20Guide.pdf. (accessed 27 June 2022).

4. Tello. SDK 3.0. *Ryze Tech Support*, 2021. 10 p. Available at: https://dl.djicdn.com/downloads/RoboMaster+TT/Tello_SDK_3.0_User_Guide_en.pdf. (accessed 27 June 2022).

5. Giernacki, W., Skwierczyński, M. et al. Crazyflie 2.0 quadrotor as a platform for research and education in robotics and control engineering. *22nd International Conference on Methods and Models in Automation and*

Robotics (MMAR). Miedzyzdroje, 2017, pp. 37-42. DOI: 10.1109/MMAR.2017.8046794.

6. Noordin, A., Basri, M. A. M., Mohamed, Z. Simulation and experimental study on PID control of a quadrotor MAV with perturbation. *Bulletin of Electrical Engineering and Informatics*, 2020, vol. 9, no. 5, pp. 1811-1818. DOI: 10.11591/eei.v9i5.2158.

7. Ryze Tello Drone Support from MATLAB. Access mode: https://www.mathworks.com/hardware-support/tello-drone-matlab.html (accessed 27 June 2022).

8. Chen, S., Zhou, W., Yang, A.-S., Chen, H., Li, B., Wen, C.-Y. An End-to-End UAV Simulation Platform for Visual SLAM and Navigation. *Aerospace*, 2022, vol. 9 (2), no. 48. DOI: 10.3390/aerospace9020048.

9. Roggi, G., Meraglia, S., Lovera, M. Leonardo Drone Contest 2021: Politecnico di Milano team architecture. *International Conference on Unmanned Aircraft Systems (ICUAS).* Dubrovnik, Croatia 2022, pp. 676-685. DOI: 10.1109/ICUAS54217.2022.9836103.

10. Aguilar, W. G., Morales, S. G. 3D environment mapping using the Kinect V2 and path planning based on RRT algorithms. *Electronics*, 2016, vol. 5, no. 4. pp. 70-87. DOI:10.3390/electronics5040070.

11. Casado, R., Bermúdez, A. Framework for Developing Autonomous Drone Navigation Systems. *Electronics*, 2021, vol. 10, no. 7. DOI: 10.3390/electronics10010007.

12. Naumenko, I., Myronenko, M., Savchenko, T. Information-extreme machine training of on-board recognition system with optimization of RGB-component digital images. *Radioelectronic and Computer Systems*, 2021, no. 4, pp. 59-70. DOI: 10.32620/reks.2021.4.05.

13. Sarkar, S., Totaro, M. W., Elgazzar, K. Intelligent drone-based surveillance: application to parking lot monitoring and detection. *Unmanned Systems Technology XXI*, article no. 11021, pp. 13-19. DOI: 10.1117/12.2518320.

14. Dragomir, M., Maer, V.-M., Buşoniu, L. The Co4AIR Marathon – A Matlab Simulated Drone Racing Competition. *2022 International Conference on Unmanned Aircraft Systems (ICUAS).* Dubrovnik, 2022, pp. 1219-1226. DOI: 10.1109/ICUAS54217.2022.9836233.

15. Kadhim, E. H., Abdulsadda, A. T. Mini Drone Linear and Nonlinear Controller System Design and Analyzing. *Journal of Robotics and Control (JRC)*, 2022, vol. 3, no. 2, pp. 212-218. DOI: 10.18196/jrc.v3i2.14180.

16. Ceppi, P. *Model-based Desi gn of a Line-tracking Algorithm for a Low-cost Mini Drone through Vision-based Control.* Thesis for the degree of Master of Science. Turin, 2021. 163 p. Available at: https://webthesis.biblio.polito.it/16018/1/tesi.pdf (accessed 12 June 2022).

17. Akhloufi, M. A., Arola, S., Bonnet, A. Drones Chasing Drones: Reinforcement Learning and Deep Search Area Proposal. *Drones*, 2019, vol. 3, no. 3, article no. 58, pp 1-14. DOI: 10.3390/drones3030058.

18. Chen, B., Hua, C., Li, D., He, Y., Han, J. Intelligent Human – UAV Interaction System with Joint Cross-Validation over Action – Gesture Recognition and Scene Understanding. *Applied Sciences*, 2019, vol. 9, iss. 16, article no. 3277. DOI: 10.3390/app9163277.

19. Santhiya, R., GeethaPriya, C. Machine Learning Techniques for Intelligent Transportation Systems-An overview. *12th International Conference on Computing Communication and Networking Technologies (ICCCNT).* Kharagpur, 2021, pp. 1-7. DOI: 10.1109/ICCCNT51525.2021.9579970.

20. Girisha, S., Manohara Pai, M. M., Verma, U., Pai, R. M. Semantic segmentation of UAV aerial videos using convolutional neural networks. *IEEE Second International Conference on Artificial Intelligence and Knowledge Engineering (AIKE).* Sardinia, 2019, pp. 21-27. DOI: 10.1109/AIKE.2019.00012.

21. Lyu, Y., Vosselmana, G., Xia, G.-S., Yilmazc, A., Ying Yang, M. UAVid: A semantic segmentation dataset for UAV imagery. *ISPRS journal of photogrammetry and remote sensing*, 2020, vol. 165, pp. 108-119. DOI: 10.1016/j.isprsjprs.2020.05.009.

22. Bartolomei, L., Teixeira, L., Chli, M. Perception-aware path planning for UAVs using semantic segmentation. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).* Las Vegas, 2020, pp. 5808-5815. DOI: 10.1109/IROS45743.2020.9341347.

23. Patel, M. J., Kothari, A.M., Koringa, H. P., A novel approach for semantic segmentation of automatic road network extractions from remote sensing images by modified UNet. *Radioelectronic and Computer Systems*, 2022, no. 3, pp. 161-173. DOI: 10.32620/reks.2022.3.12

24. Kritskiy, D., Pohudina, O. Object recognition to refine drone positioning. *IEEE 15th International Conference on Computer Sciences and Information Technologies (CSIT)*, Zbarazh, Ukraine, 2020, pp. 82-85. DOI: 10.1109/CSIT49958.2020.9321945.

Надійшла до редакції 27.06.2022, розглянута на редколегії 20.02.2023

МЕТОД ЗАБЕЗПЕЧЕННЯ АВТОНОМНОГО ПОЛЬОТУ БЕЗПІЛОТНОГО ЛІТАЛЬНОГО АПАРАТУ PARROT MAMBO З ВИКОРИСТАННЯМ ДАНИХ СЕМАНТИЧНОЇ СЕГМЕНТАЦІЇ

Давід Насо, Ольга Погудіна, Сергій Яшин,
Андрій Погудін, Росселла Бартоло

За останнє десятиліття автономна навігація безпілотних літальних апаратів (БПЛА) є надзвичайно привабливою темою, у тому числі через підвищення доступності обладнання та програмного забезпечення з відкритим вихідним кодом для керування та обробки даних. Попит на дані технології викликав великий інтерес

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

до розробки доступних експериментальних платформ для навчання студентів інженерних спеціальностей в швидко розвиваючій галузі автономної навігації. У цій статті ми описуємо платформу, що базується на недорогому обладнанні, яка використовує переваги середовища програмування Matlab/Simulink для вирішення проблем, пов'язаних з автономною навігацією БПЛА. Зокрема, предметом цієї статті є автономне керування польотом невеликого БПЛА, який має досліджувати та патрулювати невідоме середовище в приміщені. Завдання: проаналізувати існуючі апаратні платформи для автономного польоту в приміщенні, вибрати стратегію автономного польоту для дослідження невідомих приміщень, формалізувати процедуру отримання моделі знань для семантичної класифікації приміщень, формалізувати отримання відстані до перешкод за допомогою камери, що встановлено горизонтально і побудови карти перешкод. А саме, ми використовуємо: метод сегментації зображення на основі порогу яскравості, метод навчання мережі семантичної сегментації, алгоритми переміщення, що засновано на стохастичних моделях робототехніки. Ми розглядаємо як випадок навігації, заснованої на структурованій візуальній інформації, розміщеній у навколишньому середовищі, наприклад, контрастні маркери для польоту (наприклад, червона маркер-стрічка над якою здійснюється політ), так і випадок навігації, заснованої на неструктурованій інформації: такі як об'єкти, що розпізнаються, або жести людей. На підставі попередніх випробувань найбільш підходящим методом автономної навігації у приміщенні є класифікація та сегментація об'єктів, щоб БПЛА поступово аналізував навколишні об'єкти у приміщенні та приймав рішення щодо планування своєї траєкторії. Результатом нашого дослідження є метод, який підходить для забезпечення автономного польоту БПЛА із фронтальною відеокамерою. Висновки. Наукова новизна одержаних результатів полягає в наступному: удосконалено метод автономного польоту малих БПЛА за рахунок використання семантичної мережевої моделі та визначення мети польоту лише на заданій висоті для мінімізації обчислювальних витрат обмежених можливостей автопілоту недорогих моделей малих БПЛА. Результати нашого дослідження можуть бути розширені шляхом проведення серії експериментів для різних умов.

Ключові слова: безпілотні літальні апарати; згорткова нейронна мережа; семантична сегментація; система керування польотом; сітка зайнятості.

Давід Насо – PhD, проф., зав. лаб. робототехніки кафедри електротехніки та інформаційної техніки, Політехнічний університет Барі, Італія.

Ольга Погудіна – канд. техн. наук, доц., доц. каф. інформаційних технологій проєктування, Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут», Харків, Україна.

Сергій Яшин – старш. наук. співроб. каф. інформаційних технологій проєктування, Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут», Харків, Україна.

Андрій Погудін – PhD, доц. каф. космічної техніки та нетрадиційних джерел енергії Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут», Харків, Україна.

Росселла Бартоло – PhD, наук. співроб. каф. механіки, математики, менеджменту, Політехнічний університет Барі, Італія.

David Naso – PhD, Full Professor, Head of the Robotics Lab at the Department of Electrical and Information Engineering, Politecnico di Bari, Italy,
e-mail: david.naso@poliba.it, ORCID: 0000-0002-7948-8226, Scopus Author ID: 6602866170.

Olha Pohudina – Candidate of Technical Sciences, Assistant Professor of the Department of Information Technology Design, National Aerospace University “Kharkiv Aviation Institute“, Kharkiv, Ukraine,
e-mail: ok.pogudina@gmail.com, ORCID: 0000-0001-5689-2552, Scopus Author ID: 57204907264.

Andrii Pohudin – PhD, Assistant Professor of the Department of Space Technology and Non-Traditional Energy Sources, National Aerospace University “Kharkiv Aviation Institute“, Kharkiv, Ukraine,
e-mail: andrey.pohudin@gmail.com, ORCID: 0000-0002-8673-2119, Scopus Author ID: 57214223045.

Sergiy Yashin – senior researcher of the Department of Information Technology Design, National Aerospace University “Kharkiv Aviation Institute“, Kharkiv, Ukraine,
e-mail: sergey.yashin.xai@gmail.com, ORCID: 0000-0002-1680-4156, Scopus Author ID: 57219053677.

Rossella Bartolo – Ph. D. cum laude in Mathematics (Geometry and Topology Department), Researcher of the Department of Mechanics, Mathematics, Management, Politecnico di Bari, Italy,
e-mail: rossella.bartolo@poliba.it, ORCID: 0000-0002-7230-9651, Scopus Author ID: 7004507482