ДОДАТОК А

Код програми

```
import cv2
from ultralytics import YOLO
import numpy as np

# Ініціалізація моделі YOLOv8
model = YOLO("yolov8n.pt")  # Можна замінити на свою треновану

# Запускаємо відео з камери (або змінити номер/потік)
cap = cv2.VideoCapture(1)

# Список об'єктів для трекінгу: {obj_id: {"path": [...], "label": str}}
tracked_objects = {}
next_object_id = 0

# Параметри для відстеження
tracker_type = cv2.TrackerKCF_create

# Ініціалізація трекерів
active_trackers = []

while True:
    ret, frame = cap.read()
    if not ret:
        break

    # Виконуємо детекцію
```

```
results = model(frame, verbose=False)
boxes = results[0].boxes.xyxy.cpu().numpy() if results[0].boxes is not None else []
labels = results[0].boxes.cls.cpu().numpy() if results[0].boxes is not None else []

# Якщо немає активних трекерів, створюємо нові
if len(active_trackers) == 0:
    for box, cls_id in zip(boxes, labels):
        x1, y1, x2, y2 = map(int, box)
        tracker = tracker_type()
        tracker.init(frame, (x1, y1, x2 - x1, y2 - y1))
        active_trackers.append((tracker, next_object_id))
        label = model.names[int(cls_id)]
        tracked_objects[next_object_id] = {"path": [(int((x1 + x2) / 2), int((y1 + y2) / 2))], "label": label}
        next_object_id += 1
else:
    # Оновлюємо трекери
    new_trackers = []
    for tracker, obj_id in active_trackers:
        success, box = tracker.update(frame)
        if success:
            x, y, w, h = map(int, box)
            center = (x + w // 2, y + h // 2)

            tracked_objects[obj_id]["path"].append(center)

            # Малюємо прямокутник
            cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 255, 0), 2)
```

```
                # Підписуємо клас
                label_text = tracked_objects[obj_id]["label"]
                cv2.putText(frame, label_text, (x, y - 10), cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 255, 0), 2)

                # Малюємо траєкторію
                for i in range(1, len(tracked_objects[obj_id]["path"])):
                    cv2.line(frame, tracked_objects[obj_id]["path"][i - 1], tracked_objects[obj_id]["path"][i], (0, 0, 255), 2)

                new_trackers.append((tracker, obj_id))

        active_trackers = new_trackers

    cv2.imshow("YOLOv8 FPV Tracking", frame)
    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

cap.release()
cv2.destroyAllWindows()
```

ДОДАТОК Б

Апробація результатів кваліфікаційної роботи

Міністерство освіти і науки України

Харківський національний університет радіоелектроніки

Кафедра комп'ютерно-інтегрованих технологій, автоматизації та робототехніки

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Виробництво & Мехатронні Системи 2025: матеріали IX-ої Міжнародної конференції, Харків, 25-26 жовтня 2025 р.: тези доповідей / [редкол. І.Ш. Невлюдов (відповідальний редактор)].-Харків: [електронний друк], 2025. – 115 с.

У збірник включені тези доповідей, які присвячені сучасним тенденціям розвитку технологій та засобів виробництва та мехатронних систем, передовому досвіду та впровадженню їх в галузях систем промислової автоматизації та керування виробництвом; системній інженерії; CAD/CAM/CAE системах; мехатроніці (електро-механічних системах, електронних інструментах систем керування, механічних CAD системах); робототехніці та засобахм інтелектуалізації; MEMS (сучасних матеріалів та технологіях виготовлення MEMS) та компонентах і технологіях автоматизації видобутку, переробки та транспортування нафти та газу.

Редакційна колегія: І.Ш. Невлюдов, В.В. Євсєєв.

Manufacturing & Mechatronic Systems 2025: Proceedings of IX st International Conference, Kharkiv, October 25-26, 2025: Thesises of Reports / [Ed. I.Sh. Nevlyudov (chief editor).] .- Kharkiv .: [electronic version], 2025. - 115 p.

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Editorial board: Igor.Sh. Nevludov, Vladyslav.V. Yevsieiev

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Analysis of object identification methods for FPV drones

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Abstract: The abstracts of the report consider modern methods of object identification for FPV drones with an emphasis on their application in real time and under conditions of limited computing resources. Classical approaches based on keypoint extraction, deep convolutional neural networks, semantic and instance-segmentation methods, as well as state filters and lightweight optimized models are analyzed. The study shows that each of the methods has its advantages and limitations depending on the accuracy, processing speed and complexity of the environment. Special attention is paid to hybrid approaches that combine the advantages of several methods to ensure stable and effective object identification on board FPV drones. The results obtained emphasize the need to optimize algorithms and adapt models to the resource constraints of drones to ensure reliability and accuracy of operation in dynamic conditions.

Keywords: FPV drones, object identification, computer vision, deep neural networks, segmentation, Kalman filter, lightweight models, hybrid methods, real-time.

I. Introduction

The modern development of unmanned aerial vehicles, in particular FPV drones, opens up new opportunities for their use in military, civil and industrial spheres, where fast and reliable identification of objects in real time plays a key role. FPV technology provides the operator with the ability to directly visually control the drone, which allows performing complex maneuvers, however, the effectiveness of task performance largely depends on the accuracy of the object recognition system. In conditions of a dynamic environment, changes in lighting, the presence of obstacles or camouflage, target identification becomes a particularly difficult task. This necessitates the use of modern methods of computer vision, machine learning and deep neural networks, which are able to improve the quality of recognition even with incomplete or distorted data. The importance of this direction is determined by the need to increase the autonomy of FPV drones, which will reduce dependence on the operator and increase efficiency in performing reconnaissance, search and rescue or tactical tasks. At the same time, it is relevant to study methods for object identification from the point of view of optimizing computing resources, since FPV drones usually have limited computing power. Thus, analyzing existing approaches and determining their advantages and disadvantages is an important stage for the further development of intelligent decision support systems in the field of FPV technologies.

II. Mathematical Description of Methods for Controlling a Group of Mobile Robots

Feature-based keypoint detection & matching (SIFT / ORB / BRIEF) method. This is a classic approach that extracts local "keypoints" in frames, builds descriptors for them, and compares the descriptors between frames or with a sample database to identify objects; works well with limited resources and changing object appearance. Mathematically, the key steps are: feature detection through local operations on the image (e.g., Difference of Gaussians - DoG) and descriptor construction (gradient histograms in SIFT or binary comparisons in BRIEF/ORB).

- DoG for detection:

$$\begin{gathered} L(x,y,\sigma) = G(x,y,\sigma)\cdot I(x,y) \\ DoG(x,y,\sigma_k) = L(x,y,k_\sigma) - L(x,y,\sigma) \end{gathered} \tag{1}$$

Where: G - Gaussian filter with dispersion σ; I - intensity; σ - scale, detection threshold, number of octaves

- ORB/BRIEF descriptor + matching:

$$D(d_a, d_b) = Hamming\ (d_a, d_b) \tag{2}$$

Advantages: few computations (especially ORB/BRIEF), invariance to shift/scale/rotation (SIFT), works well with scarce resources and for real-time on edge platforms. Disadvantages: sensitivity to strong lighting changes, texture-poor regions (where there are few keypoints), difficult to scale to semantic identification (class ≠ specific keypoint).

Method one-stage detectors based on CNN (YOLO / SSD). These models implement object detection and classification in a single pass of the network, estimating for each anchor rectangle the coordinates and class probabilities; suitable for fast processing of FPV video with sufficient hardware support (GPU / NN-accelerator). Mathematically — convolutions + box regression + loss functions for coordinates and probabilities (combination of local regression and cross-entropy). Model (basic architecture):

$$\begin{gathered} y = f_\theta(I) \\ L = \lambda_{coord}\sum(x-\hat{x})^2 + \lambda_{coord}\sum(y-\hat{y})^2 \\ + \sum CE(p_{class}, \hat{p}_{class}) + \cdots \end{gathered} \tag{3}$$

Where: f_θ - convolutional network.

Advantages: high speed (especially YOLO-lite versions), ready-made end-to-end solutions, good balance of accuracy and speed. Disadvantages: for FPV drones, requires optimization/hardware acceleration; accuracy drops for very small or very blurred objects; demanding on the amount of training data.

Method semantic segmentation / instance segmentation (U-Net, DeepLab, Mask R-CNN). The method returns object masks (pixel identification) and is useful when you need to accurately separate the shape of an object in an FPV frame (for example, people, cars, useful details). The mathematics is based on convolutional network transformations with upsampling (decoder) and a loss function per pixel (cross-entropy or IoU-based loss).

- model 1 (U-Net):

$$y = Decoder(Encoder(I)) \tag{4}$$

where the encoder compresses the image properties, the decoder restores the mask size; parameters: number of levels, filter size, activation function.

- model 2 (IoU-loss for mask):

$$L_{IoU} = 1 - \frac{\sum p_i g_i}{\sum p_i + \sum g_i - \sum p_i g_i} \tag{5}$$

Where: p_i - predicted pixels; g_i – true.

Advantages: accurate localization and shape of the object, useful for navigating around static/dynamic obstacles. Disadvantages: high computational and memory requirements; slower than box detectors; more difficult in real-time on limited FPV drone hardware.

Tracking + state estimation method (Kalman Filter, Particle Filter + association - SORT/DeepSORT). This approach combines frame-by-frame detection with tracking of object trajectories over time, which allows maintaining object identity during short-term fading or partial overlaps. The mathematics consists of state filter equations and prediction/correction steps and an association algorithm between detections and tracks (e.g., guessing/Hungarian algorithm). Model (Kalman filter, linear):

- state:

$$x_{t+1} = Fx_t + Bu_t + w_t \tag{6}$$

- observation:

$$z_t = Hx_t + v_t \tag{7}$$

Where: $w_t \sim \mathcal{N}(0, Q)$; $v_t \sim \mathcal{N}(0, R)$; H – observation matrix; Q, R - noise covariance. Particle filter is suitable for nonlinear/non-Gaussian cases where the state is approximated by a set of particles $\{x^{(i)}, w^{(i)}\}$. Association: minimization of the cost matrix (IOU or distance) via Hungarian; parameters: IOU threshold, maximum track loss. Advantages: stability of tracks over time, possibility of predicting object motion and recovery after losses. Disadvantages: dependence on detector quality, association errors with strong crowding of objects; Particle filter can be computationally expensive.

Method Lightweight on-device models and optimizations (MobileNet, EfficientNet-Lite + quantization/pruning/distillation). For FPV drones, it is critical to reduce computation and memory, so specially optimized architectures and model compression techniques are used. Mathematically important idea is depthwise separable convolutions (MobileNet), which decompose the full convolution into depthwise and pointwise stages, significantly reducing the number of operations. Model (depthwise separable conv): the full convolution has a complexity:

$$D_k^2 \cdot M \cdot N \cdot H \cdot W \tag{8}$$

Where: D_k - kernel size; M - input channels; N - output; parameters: network width (width multiplier), input resolution, quantization degree (8-bit, 16-bit). Quantization is also used: $w_q = round(\frac{w}{s})$ with scale s, and pruning (removal of small weights). Advantages: the ability to perform inference directly on board a drone with limited energy consumption, low latency, maintaining autonomy. Disadvantages: tradeoff of accuracy against size/speed; some optimizations (aggressive pruning, low-bit quant) can spoil stability for delicate classes.

General conclusion: all the described approaches have their strengths and limitations - classical feature-based methods are light and cheap in resources, but weak in semantic classification; CNN detectors provide powerful semantics and speed, but require optimization for FPV drones; segmentation is useful for accurate localization of shapes, but is more resource-intensive; the combined approach "detection + tracking/state filtering" significantly increases the robustness of identification in the video stream; and the use of lightweight architectures and compression techniques is a mandatory practical step for implementing an identification system directly on a drone. For FPV scenarios, hybrid solutions are most effective: for example, a lightweight CNN detector on board + segmentation/more accurate validation on the backend or a hardware accelerator; or a combination of feature-matching for fast matches and CNN for class confirmation. If you want, I can: a) offer examples of architectures (MobileNet-Tiny + SSD configurations) with approximate calculation metrics; b) prepare a flowchart of on-board / off-board processing integration for an FPV drone - immediately in technical form.

III. COMPARATIVE ANALYSIS OF METHODS FOR CONTROLLING A GROUP OF MOBILE ROBOTS

A comparative analysis of the considered methods of object identification for FPV drones shows that each of them has its own implementation specifics, which are determined by both mathematical models and hardware limitations of the platforms themselves. Classical computer vision methods based on feature extraction, in particular SIFT or ORB, are characterized by relative simplicity of implementation and low requirements for computing resources, which makes them suitable for FPV drones with limited on-board processor performance. At the same time, these methods are vulnerable to changes in lighting, noise and partial overlaps, which significantly reduces their reliability in dynamic and unpredictable conditions. Deep convolutional neural networks, on the contrary, provide high accuracy of object recognition even in complex environments, but require significant computing power and optimization, in particular through the use of accelerators such as GPU or TPU. For FPV drones, where energy efficiency and processing speed are critical, CNN models require special optimizations, for example, by using MobileNet or Tiny-YOLO. Bayesian methods, in particular variations of the Kalman filter or particle filters, provide good performance in conditions of noisy sensor data and partial visibility of objects, allowing to integrate information from multiple sources. However, their effectiveness depends on the correct definition of a priori models and probability distributions, which is sometimes a difficult task in real flight conditions. Methods based on fuzzy logic demonstrate flexibility in cases where the data is imprecise or contradictory, but their accuracy and speed may be inferior to other current approaches. Bio-inspired algorithms, such as swarm models or evolutionary approaches, allow FPV drones to distribute the load and collectively identify objects, but when used alone they do not provide high accuracy without integration with more traditional methods. In general, it can be noted that for FPV drones, the most effective are hybrid systems that combine the simplicity of classical methods for pre-extraction of features with the high accuracy of deep models, as well as support the results with probabilistic and fuzzy methods. This allows you to balance computational costs, energy efficiency and recognition quality, which is critical for performing tasks in real time.

IV. Conclusion

The conducted study of object identification methods for FPV drones showed that the efficiency of such systems largely depends on the choice of algorithmic approach and hardware platform. Classical methods based on key points, such as SIFT and ORB, provide relatively low computational complexity and fast operation, but their accuracy is significantly reduced in conditions of noise, lighting changes or partial overlapping of objects. Deep convolutional neural networks allow achieving high recognition accuracy even in complex dynamic scenes, but require optimization for use on board FPV drones due to limited computing resources. Semantic and instance-segmentation methods provide accurate selection of the object shape and are useful for navigation, but are more resource-intensive and slower in real time. The use of state filters, such as Kalman or particle filters, together with tracking allows maintaining the identity of the object over time and predicting its movement, but requires a correct a priori model and parameter settings. Lightweight optimized models such as MobileNet and EfficientNet-Lite with quantization and pruning techniques demonstrate a balance between speed and accuracy, making them suitable for on-board processing on FPV drones. The overall analysis shows that the most effective are hybrid approaches that combine classical feature extraction methods with deep models and probabilistic filters to increase the robustness and accuracy of identification. This approach allows for optimal allocation of computing resources, ensuring fast real-time response and system reliability in dynamic environments. The implementation of hybrid methods is promising for the development of autonomous FPV drones that perform reconnaissance, monitoring and navigation tasks in complex conditions. The results obtained emphasize the need for further improvement of algorithms, integration of optimized models and development of adaptive systems capable of operating in various environments with a high level of uncertainty.

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ДОДАТОК В

Демонстраційний матеріал

№ документа	Позначення	Найменування	Додаткові відомості
		<u>Текстові документи</u>	
1	ГЮИК. 432361.014 ПЗ	Пояснювальна записка	А4, 87 с.
		<u>Додаткові матеріали</u>	
2		Демонстраційний матеріал у виляді презентації	А4, 14 с.

Змін	Арк	№ документу	Підпис	Дата	ГЮИК. 432361.014 ПЗ			
Розробив		Чебанчик Д.О.			Розроблення програмного модуля ідентифікації об'єктів для FPV дрона	Літер	Аркуш	Аркуш
Перевірив		Євсєєв В.В.				Н	1	1
						Кафедра КІТАР ХНУРЕ		
Норм. контроль		Стародубцев М.Г.						
Затвердив		Невлюдов І.Ш.						