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Unmanned ground vehicle for swampy area reconnaissance with unmanned aerial vehicle support: A conceptual framework

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ABSTRACT

This paper explores the application of unmanned vehicles for reconnaissance purposes, specifically to verify potential threat in inaccessible and swampy areas. The study introduces a novel integration of unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) with AI-driven fire detection algorithms, enabling automated wildfire monitoring in sensitive ecosystems. The proposed framework enhances terrain adaptability by optimizing nominal ground pressure for UGV mobility and limple-mentation UAV-based computer vision for real-time risk assessment. Nowadays, the supervision of ecosystems has acquired significance, with a special focus on the man-agement of national parks. One the largest areas is Biebrza National Park, sprawls across 59.223 hectares, preserving pristine wetland ecosystems and housing remarka-ble biodiversity. Regular patrols are essential to enforce regulations and thwart illegal activities. It should be highlighted that destructive fire in the year 2020 ravaged a por-tion of the park, emphasizing the need for comprehensive monitoring and protection. This work aligns with conservation policies by enabling data-driven interventions for wildfire risk mitigation. Integrating unmanned platforms and remote sensing with artificial intelligence (AI) algorithms allows national park safety improvement. This study analyzes the movement requirements of ground platforms in swampy and marshland areas and explores the reliability requirements for UAVs. Additionally, metrics for fire threat detection are discussed.

Keywords: tracked vehicle, UGV, monitoring, UAV, fire recognition, UGV/UAV cooperation.

INTRODUCTION

Biebrza National Park, located in Poland, is the country's largest national park, spanning an area of 59.223 hectares. This vast wetland ecosystem serves as a critical habitat for wildlife but is increasingly vulnerable to various environmental threats, notably wildfires. The devastating fire in 2020, which affected approximately 10% of the park's landscape, highlighted this vulnerability. More recently, another wildfire erupted in April 2025, further emphasizing the urgent need for robust and continuous environmental monitoring systems [1, 2]. These recurrent incidents have intensified interest in advanced surveillance and rapid-response technologies capable of operating in the park's difficult and diverse terrain. A promising direction to address these challenges involves the cooperative deployment of Unmanned Ground Vehicles and Unmanned Aerial Vehicles for reconnaissance and remote patrolling tasks. UGVs, equipped with advanced sensors and imaging systems, are particularly capable of traversing the park's heterogeneous and often inaccessible terrain, enabling close-range data collection where human access is limited [3–4]. On the other hand UAVs offer expansive aerial surveillance, supporting real-time monitoring of large areas and enabling early identi-fication of environmental hazards such as fire outbreaks [5–6]. The integration of these two platforms provides complementary perspectives – ground-level detail and aerial oversight – essential for improving situational awareness and facilitating prompt re-sponses to emerging threats. Recent advancements in UAV-UGV cooperative systems have significantly ex-panded their operational effectiveness in complex, unstructured environments. For in-stance, a finite-time cooperative formation control strategy for heterogeneous UAV-UGV teams has been proposed, ensuring system stability and convergence even under actuator faults or external disturbances, thus increasing operational robustness [7–9]. Additionally, a vision-aware cooperative target localization framework has been developed, employing multi-feature fusion for improved detection accuracy and resil-ience under outdoor conditions. This framework effectively merges aerial and terres-trial visual inputs to improve environmental perception [10].

In parallel, considerable progress has been made in improving communication ef-ficiency and reliability, which is especially critical in dynamic and band-width-constrained environments like the wetlands of Biebrza National Park. New methods and algorithms have been proposed to ensure reliable data exchange under fluctuating connectivity conditions [11]. Moreover, researchers have advanced tele-operation capabilities by integrating real-time perception feedback, addressing chal-lenges posed by limited visibility and degraded sensor data in swampy terrain [12].

In addition to cooperative UAV-UGV systems, recent innovations in computer vi-sion and AI-driven perception systems have shown promise for enhancing fire de-tection and environmental monitoring. Image-based fire detection techniques, pow-ered by deep learning, have emerged as a powerful tool for non-contact sensing in complex environments. These technologies, supported by advances in big data and high-performance computing (such as Graphics Processing Units or GPUs), enable re-al-time monitoring and early detection of fire hazards, even in large, difficult-to-access areas like Biebrza National Park [13]. The integration of these advanced technologies into UAV-UGV systems can significantly improve the park's capacity to respond to wildfires, poaching, and other threats..

Nevertheless, deploying these technologies in wetland environments remains challenging. The terrain is often swampy, densely vegetated, and irregular, posing se-rious mobility and perception difficulties for both aerial and ground platforms. Crucial challenges include managing multi-modal perception, achieving efficient real-time sensor data fusion, and ensuring terrain-adaptive locomotion.

TERRAIN CHALLENGES AND MISSION REQUIREMENTS

Selecting the right platforms for working in swampy areas comes with the specific operational challenges. These regions have mushy, uneven terrain and dense plants, making it hard for regular vehicles to move around. It's important that these platforms can float or move easily in the water, and they should be gentle on the environment since

Figure 1. Example of environmental limitation for patrol missions

swamps are often delicate ecosystems. Keeping them in good shape in the wet and sometimes corrosive environment can be a challenge (Figure 1). In addressing these challenges, the application of remote-controlled platforms equipped with specialized sensors and tools, such as thermal cameras, lidars, radars, and ground sampling devices, is highly anticipated. Through these un-manned plat-forms, comprehensive surveys and data collection can be conducted without exposing individuals to risk. For instance, potential fire sources can be detected by thermal cameras, and vital insights into the environment can be gleaned by ground samplers. By employing these cutting-edge technologies, the safety of individuals and the preservation of the park, especially during unforeseeable events like wildfires, can be ensured.

In this context, the development of comprehensive solutions is essential to facili-tate the adaptation of existing UGV platforms that collaborate with UAVs for effective reconnaissance missions.

SELECTION OF GROUND PLATFORM

Patrol missions in environmentally sensitive areas such as Biebrza National Park are often constrained by challenging terrain and ecological considerations. Swampy soils, dense vegetation, and low soil-bearing capacity significantly limit access to cer-tain regions, necessitating the selection of ground platforms specifically suited for re-connaissance and emergency missions. These platforms must not only ensure reliable mobility across diverse and difficult terrains but also minimize environmental impact to preserve the park's fragile ecosystems.

Efficient ground platform selection is critical for addressing these operational constraints. Emergency and extraordinary situations often demand access to areas that conventional vehicles cannot navigate due to the unstable soil conditions and the presence of natural obstacles. This study focuses on selecting ground platforms by an-alyzing the effects of tire width, the use of tracks, and load mass on nominal ground pressure.

The sensitivity of forest soils to compaction requires careful evaluation of multiple factors, including vehicle contact pressure, soil texture, moisture content, skeletal par-ticle proportion, soil structure, bulk density, porosity, and humus layer thickness. In areas with restricted ground-bearing capacity, platforms equipped with semi-tracks provide significant advantages. By increasing the contact area and reducing contact pressure, semi-tracks protect the soil from compaction and displacement. They also enhance vehicle mobility by decreasing wheel slippage, rut depth, and rolling re-sistance. This leads to operational efficiency by improving payload utilization, in-creasing vehicle speed, and lowering fuel consumption. Additionally, semi-tracks im-prove lateral stability during loading, unloading, and travel, particularly on slopes, ensuring safety and reliability in challenging conditions.

Beyond the use of semi-tracks, multi-wheel platforms provide an additional ad-vantage by not only reducing soil damage through even distribution of contact pres-sure but also enabling effective mobility in challenging environments like those found in national parks. These configurations are particularly beneficial in fragile eco-sys-tems, where preserving soil integrity is paramount. By minimizing long-term envi-ronmental degradation caused by frequent operations, multi-wheel platforms offer a sustainable solution for navigating sensitive terrains [15].

Soil bearing capacity, defined as the soil's resistance to external forces exerted by vehicle wheels or tracks, is a critical factor in platform suitability. It is assessed by measuring soil settling, often quantified as rut depth, under an applied load. This ca-pacity depends on constant soil parameters, such as texture, humus content, and skel-etal particle proportion, as well as variable factors like current soil moisture. Excessive contact pressure can lead to significant soil damage, emphasizing the importance of minimizing such impacts in sensitive terrains (Table 1).

Mentioned classification system for soil strength includes categorizing it into four classes with maximum allowable contact pressures for each. This framework provides valuable guidelines for matching vehicle specifications to the soil's bearing capacity, ensuring both effective performance and environmental conservation. Nominal ground pressure, calculated using the Mellgren equation, serves as a quantitative metric for determining platform suitability in sensitive terrains [17].

Vehicle contact pressure is the ratio of a vehicle's weight to its contact surface ar-ea with the ground, reflecting its environmental suitability for operation in fragile ecosystems. Calculating contact pressure in off-road environments is challenging due to the dependence of the tire-soil contact

Table 1. Classification of soil types [16]

Soil strength classes	General description of the soil	Cone index CI, kPa	Young's moduls E, MPa	Shear strenght τ, kPa	Ground bearing capacity GBC, kPa
Strong soil	Dry sand, gravel,	>500	>60	>60	>80
Average soil	Soft mineral or iron-pan soil	300–500	20–60	20–60	60–80
Soft soil	Wet gleys and peaty soils	<300	<20	<20	40–60
Very soft soil	Wet peats	<<300	<<20	<<20	<40

area on two factors: the elastic deformation of the loaded wheel (tire characteristics and air pressure) and the plastic-elastic de-formation of the soil (granulometric content and moisture) (Figure 2).

To standardize the calculation of contact pressures and enable comparisons be-tween vehicles and equipment configurations, the concept of nominal ground pressure was introduced. This metric represents static pressure when the vehicle is at rest, based on a rigid wheel on plastic-elastic ground.

For reconnaissance purposes in the challenging environment of Biebrza National Park, the ARGO 8 × 8 platform was analyzed as a versatile amphibious utility vehicle. Widely employed in demanding terrains, including swampy areas, this platform offers adaptability through the option to operate on wheels or tracks, significantly

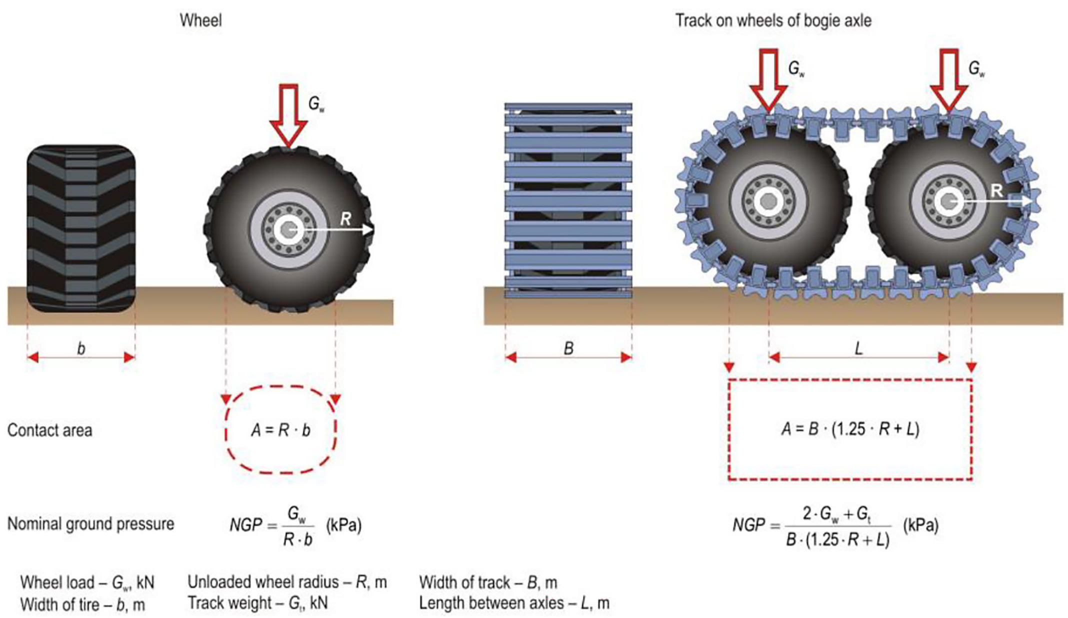

Figure 2. Calculation of ground pressure -wheels and tracks [18]

(a) (b) (c)

Figure 3. View of ARGO 8 × 8 platform: (a) and available rubber track kits (b-c)

enhancing its operational capabilities in such environments (Figure 3).

Below are listed main parameters of ARGO 8 × 8 platform [19]:

- vehicle curb weight: 603 kg,
- payload: 485 kg,
- total weight (gross): 1.088 kg (10.673 N),
- dimensions: 3023 mm (length) × 1524 mm (width) × 1169 mm (height),
- contact area:
  - wheels: assumed 0.03 m² per wheel (8 wheels in total),
  - tracks: each 2.6 m (length) × 0.45 m (width), 2 × (2.6 × 0.45) = 2.34 m²,
- ground pressure:
  - wheels: 2.1 PSI (14.5 kPa),
  - tracks: 0.67 PSI (4.6 kPa).

To evaluate platform performance on wheels and tracks the below analysis in-corporates vehicle specifications, ground pressure, and contact area calculations to determine its suitability for such challenging terrains (Table 2).

The nominal ground pressure (NGP) of the ARGO 8 × 8 was computed using the Mellgren equation, considering tracked and wheeled configurations. Figure 4 illus-trates the pressure distribution differences between the two configurations, with tracked operation significantly reducing soil displacement and improving vehicle sta-bility.

Tracks provide significantly lower ground pressure and higher traction, allowing the vehicle to traverse swampy terrain with ease. In contrast, wheels, due to higher ground pressure, generate greater soil resistance and much lower traction, making the vehicle more prone to getting bogged

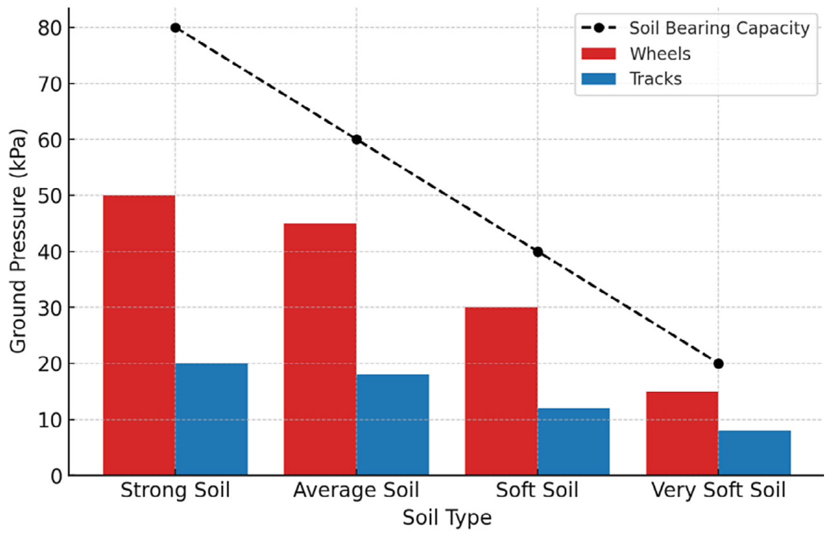

Figure 4. UGV nominal ground pressure for wheels and tracks against soil bearing capacity

Table 2. Missing title

Type of mode	Wheels	Tracks
Specific ground pressure $P = W / A$		
Total contact area	8 × 0.03 m² = 0.24 m²	2 × (2.6 m × 0.45 m) = 2.34 m²
Pressure	Pwheels = 10,673 N / 0.24 m² = 44,445.8 Pa (≈ 2.1 PSI)	Ptracks = 10,673 N / 2.34 m² = 4,564.1 Pa (≈ 0.67 PSI)
Soil resistance Fsoil = Csoil × P		
Resistance	0.5 × 44,445.8 Pa = 22,222.9 N	0.5 × 4,564.1 Pa = 2,282.05 N
Traction force Ftraction = μ × W		
Traction force	0.6 × 10,673 N = 6,402.0 N	0.8 × 10,673 N = 8,538.4 N
Vehicle mobility evaluation		
	Traction force: 6,402.0 N < soil resistance: 22,222.9 N	Traction force: 8,538.4 N > soil resistance: 2,282.05 N
	Vehicle is likely to get bogged down using wheels	Vehicle can successfully move using tracks

down in swamp conditions. Consequently, tracks are the preferred configuration for operating in challenging, swampy environments.

PROPOSED UGV/UAV COOPERATION STRUCTURE

The selected ARGO 8 × 8 ground platform, equipped with a rubber track kit, is well-suited for navigating challenging swampy terrains. However, certain areas of Biebrza National Park remain inaccessible even to this vehicle, necessitating alterna-tive reconnaissance methods to identify potential threats and enable appropriate re-sponses. A highly promising solution involves utilizing UAVs, which can operate along predefined routes to collect valuable data through onboard cameras or other suitable sensors. In the proposed framework, UGVs and UAVs work in tandem, forming a dy-namic and complementary team. Advanced communication systems enable real-time data exchange be-tween the ground and aerial units. The collaboration is orchestrated by sophisticated AI algorithms that facilitate decision-making and coordination based on the information gathered by both platforms. UGVs, with their specialized capabili-ties for ground-level navigation, venture into areas with restricted human access, navigating through wetlands, dense vegetation, and peat bogs. Simultaneously, UAVs provide a comprehensive aerial perspective, covering larger areas efficiently and cap-turing high-resolution imagery crucial for situational awareness (Figure 5).

The interaction between UGVs and UAVs is not only limited to data sharing but extends to cooperative maneuvers. The system is designed to adapt to evolving mission requirements, with the UGVs and UAVs adjusting their routes and focus areas based on real-time environmental feedback and potential threats detected by the AI algo-rithms. This dynamic cooperation structure ensures a comprehensive and adaptive approach to reconnaissance in the diverse and challenging terrains of the park.

According to proposed scenario unmanned ground platform plays an important role in navigating the challenging terrain of Biebrza National Park, conducting ground-level reconnaissance, data collection, and observation. The selected Argo 8 × 8 platform is well-suited for such demanding environments, offering exceptional off-road capabilities, as detailed in Section 3. This versatile amphibious vehicle is ca-pable of traversing swamps, muddy terrain, water bodies, and rugged landscapes. The Argo 8 × 8 is widely used in

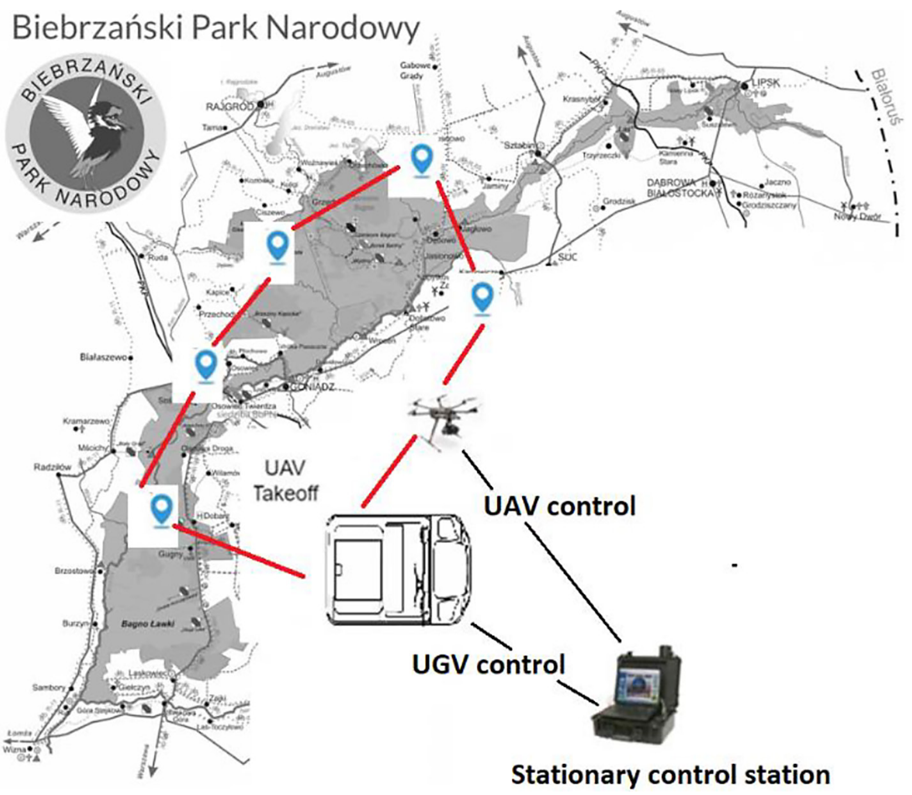

Figure 5. Reconnaissance mission scenario

outdoor applications like agricultural operations, and search-and-rescue missions due to its ability to access remote and hard-to-reach areas. Its robust design and proven durability make it ideal for enduring harsh environmen-tal conditions.

To adapt the Argo 8 × 8 for unmanned missions, it is necessary to integrate an ad-vanced control system equipped with perception sensors. These sensors improve the platform's situational awareness and environmental assessment capabilities, even in adverse weather conditions such as fog or dense smoke. This feature is particularly critical when passive sensors, like cameras, face limitations in visibility. The seamless combination of the Argo 8 × 8's rugged platform with these advanced active sensors ensures adaptability and resilience in complex operational scenarios, enabling the re-liable acquisition of critical data under challenging conditions. The already proven on-board system (Figure 6) of the unmanned platform relies on a modular design, that is robust against operational temperature variations [20]. Pro-posed architecture enables the seamless integration of additional modules, such as a reconnaissance aircraft, thereby further broadening the platform's adaptability and functionality.

This ground-based platform serves as a docking and loading system for UAVs equipped with daytime and thermal cam-eras for visual analysis. The advantage of incorporating drones lies in their exceptional agility and flight speed, which comple-ments the capabilities of the unmanned ground vehicle. While the primary function of the unmanned ground vehicle is to transport heavy loads and install sensing devices, drones ex-tend capabilities in delivering real-time situation awareness. Their ability to swiftly traverse the terrain and transmit data significantly amplifies mission effec-tiveness. Utilizing state-of-the-art technologies such as computer vision and machine learning, UAVs can scrutinize transmitted images and identify potential threats. This crucial data empowers operators to make informed decisions, adjust routes, or take essential actions to overcome both natural and deliberately positioned obstacles. This integration not only heightens situational awareness but also streamlines responses to unforeseen challenges, ultimately enhancing the safety and efficacy of missions.

In response to the specific mission requirements and the intricate challenges pre-sented by the environment of Biebrza National Park, the developed Falcon V5 coaxial quadrotor (Figure 7) was selected as UAV platform. This choice is driven by the platform's ability to address the critical issues inherent to the mission. The Falcon V5 excels in drive efficiency and lift capacity, ensuring optimal manoeuvrability through the challenging terrains, including wetlands and dense vegetation, while providing payload capacity for advanced sensors and equipment.

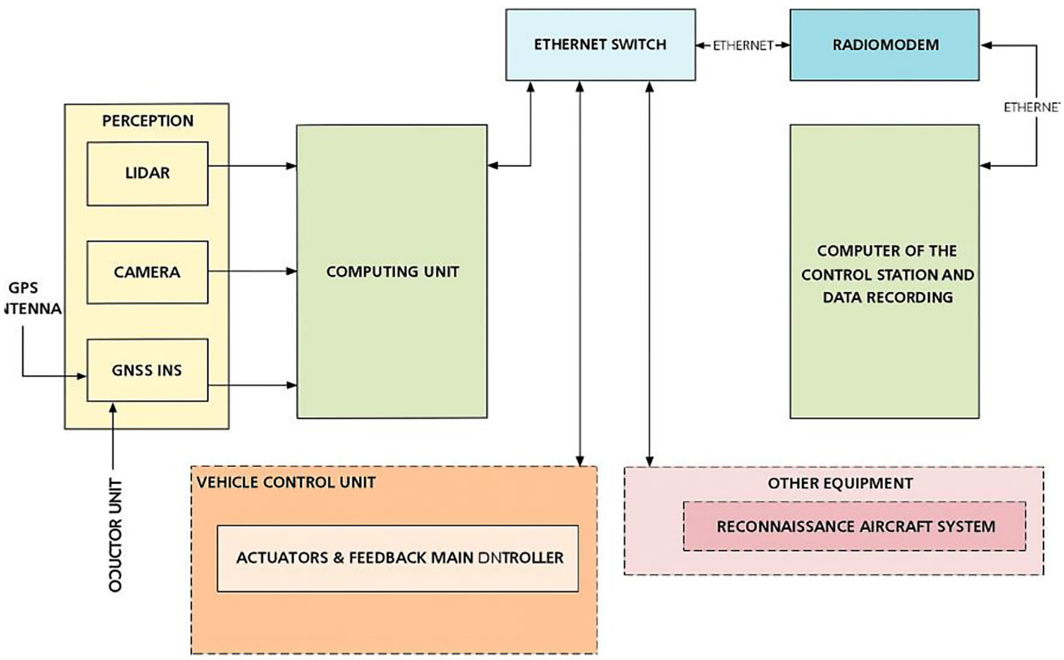

Figure 6. Block diagram of proposed control system for Argo 8 × 8 650

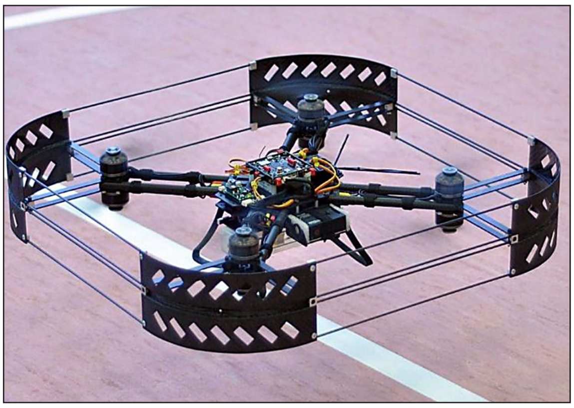

Figure 7. View of developed Falcon V5 coaxial quadrotor

The UAV's reliability is fortified by the Falcon V5's automatic fault and damage detection system, swiftly identifying potential issues. This capability facilitates prompt maintenance actions, effectively minimizing the risk of operational disruptions. Furthermore, the Falcon V5's remarkable fast reconfigurability plays a central role in seamlessly adapting to the dynamic environmental conditions within the national park and evolving mission requirements. This adaptability ensures that the UAV can swiftly and effectively respond to changes, contributing to the over-all success of the mission in Biebrza National Park.

Communication between all units is managed through a decentralized Mesh net-work (Figure 8), which is essential for missions conducted in GPS-denied or signal-degraded environments. Each UAV or UGV acts as a network node capable of re-laying information, enabling multi-hop communication without a central control unit. This structure guarantees network resilience, maintaining system integrity even if a node becomes non-functional or exits the coverage area.

Network topologies differ depending on vehicle type. UAVs typically use hierar-chical or hybrid mesh networks that support longer-range communication and maintain line-of-sight connectivity (Figure 9) through airborne relays. Conversely, UGVs rely on flat mesh architectures, which prioritize fault tolerance in terrain-constrained environments, although at the cost of higher latency. A unified mission control interface is proposed incorporating ROS-based software modules and MAVLink data input. This setup enables high-level mission planning, including UAV flight path definition, UGV route coordination, and real-time network status visualization, thereby reducing the need for continuous operator input.

The integration of ARGO 8 × 8 UGVs with Falcon V5 UAVs, supported by AI-based coordination and decentralized communication, provides a scalable and re-silient system for environmental monitoring and threat detection in Biebrza National Park.

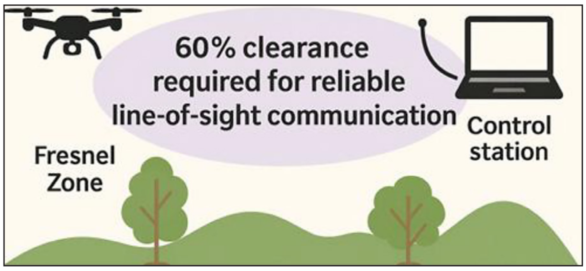

Figure 9. Fresnel zone requirements for line of sight communication

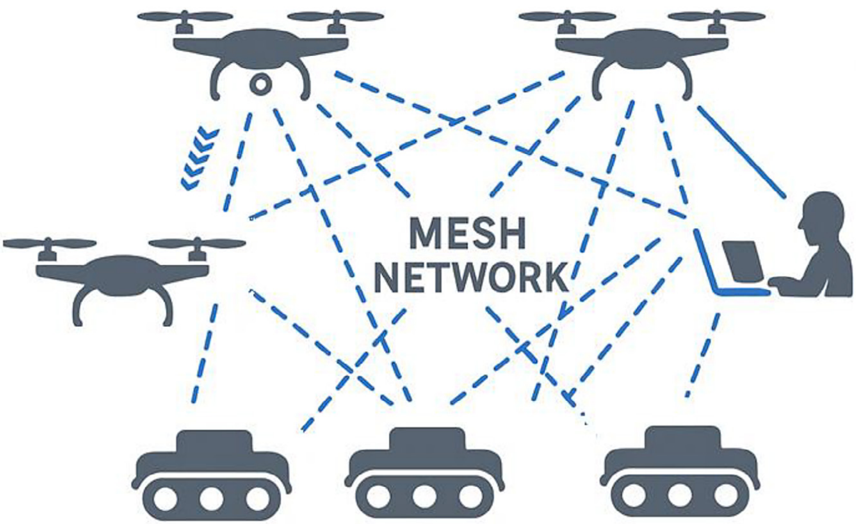

Figure 8. Mesh network structure for communication with unmanned platforms

RELIABILITY REQUIREMENTS FOR UAV FIRE FIGHTING MISSIONS

The UAV's reliability is fortified by the Falcon V5's automatic fault and damage detection system, swiftly identifying potential issues. This capability facilitates prompt maintenance actions, effectively minimizing the risk of operational disruptions. Furthermore, the Falcon V5's remarkable fast reconfigurability plays a central role in seamlessly adapting to the dynamic environmental conditions within the national park and evolving mission requirements. This adaptability ensures that the UAV can swiftly and effectively respond to changes, contributing to the over-all success of the mission in Biebrza National Park.

Based on the experience of the AeroLAB Drone Laboratory of Poznan University of Technology, to ensure the highest reliability requirements for UAV autonomous missions, the Falcon V5 drone is proposed, where an attention to following features, was paid:

a) Propulsion efficiency & maximum payload [21]:
- Falcon V5 is a custom-built aerial research platform based on the X8 plat-form quadrotor configuration (Figure 10) and custom-built avionics system. The dual propeller system allows one to continue the mission/land safely in the unexpected situation of losing one of them.
- The coaxial propulsion system is protected with carbon covers, minimizing damage of propellers and the risk of sudden landing in the event of contact with environmental elements during outdoor flights.
- The selection of propulsion units and verification of their efficiency (thrust force, lifting capacity) were carried out through experiments on a special testbed. After that self-tuning of controllers has been performed (Figure 11).

b) AI-based automatic fault and damage detection system [22]:
- The current level of robot's autonomy allows one to effectively detect damage of particular propeller, as well as anomalies (even at an early stage) in the system of the drone's propulsion units.
- Falcon is equipped with an array of directional micro-phones, the infor-mation from which is continuously processed using neural networks of long short-term memory (LSTM) type indicating the location and nature of detected problems.

c) Fast and easy reconfigurability [23]:
- The on-board avionics of the Falcon V5 robot has been made in a "sandwich" architecture, which allows it to be effectively adapted to the current fire fighting mission.
- Each module (e.g. equipped with electronic odor/smoke sensors) is plugged/unplugged into specially prepared mounting pins above the drone's on-board controller, on-board computer module, etc. – creating following layers of the sandwich. Furthermore, the Falcon V5 architecture allows for the use of RGB and infrared cameras.

d) A reliable model of drone dynamics [24]
- Rapid prototyping of new solutions is enabled by a devel-oped mathemati-cal model describing the drone flight dynamics.

PEAT BOG FIRE THREAT DETECTION

Efficient approaches for evaluating the fire risk in peat bogs and determining the directions of their spread have been under exploration. Peat fires, characterized by their prolonged duration (lasting

Figure 10. View on dual propeller system of Falcon V5

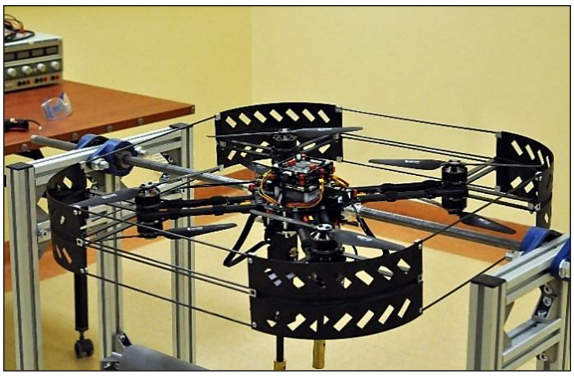

Figure 11. Testbed for UAV control system prototyping

several to multiple days), extensive reach (often cov-ering hundreds of hectares), and rapid spread at speeds of up to 20 km/h, have spurred the explo-ration of advanced and nuanced techniques.

In this paper, a solution that utilizes an UAV equipped with both RGB and infrared cameras to conduct meticulous missions in designated park sectors, is proposed. The integration of different sensors allows for a comprehen-sive capture of both visible and thermal information. The RGB imagery provides high-fidelity visual data, while the infrared component is responsible for detecting temperature variations associated with smoldering or actively burning peat. This syn-thesis of visual and thermal information significantly heightens the accuracy and reli-ability of the fire detection pro-cess.

Effective analysis can be carried out using pre-defined neural networks, enabling the auto-matic detection of areas with smoke (highlighted by yellow bounding boxes in Figure 8) and active fires (depicted in red).

These detections depend on sophisticated im-aging methods carefully tailored for precise fire detection and thorough risk assessment within the distinctive environ-mental context of peat bogs. The rise of deep learning in fire detection has been driven by the increasing volume of data, advanc-es in big data technology, and improvements in GPU performance. Deep-learning-based methods in fire detection require a substan-tial variety of samples to effectively train deep neural networks, allowing them to de-tect fire-related information at different levels of detail.

A variety of classification networks, such as CNNs (e.g., AlexNet, GoogLeNet, VGGNet, ResNet, MobileNet, and DenseNet), have been widely adopted for fire detec-tion tasks. These networks are instrumental in enhancing model robustness, enabling the identification of environ-mental characteristics with greater accuracy, and signifi-cantly reducing false cases (Figure 12).

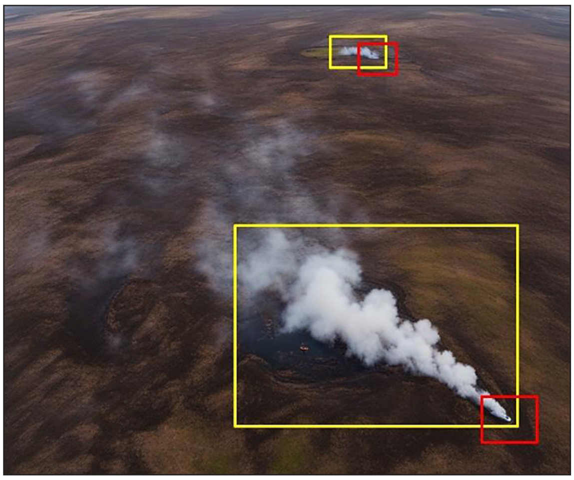

Figure 12. Example of detection of peat bog fire risk using machine learning based on vision methods

A method based on the lightweight network SqueezeNet [25] was incorporated as the back-bone network for video fire detection. The archi-tecture was fine-tuned with smaller convo-lution-al kernels and the exclusion of dense fully con-nected layers, demonstrating increased efficiency in model size and inference speed. Additionally, an algorithm was developed to extract fire-sensi-tive feature maps from the convolutional layers, facilitating a detailed analysis of flame propa-gation and helping assess the fire's intensity. A deep multi-scale CNN (DMCNN) for smoke recognition [20] was proposed to incorporate the multi-scale convolutional structure of Inception for scale invariance. This model employed multi-scale additive fusion layers to lower computation-al cost while maintaining both dynamic and static smoke features.

A lightweight fire-detection model, Light-Fi-reNet, was introduced, drawing in-spiration from the hard Swish (HSwish) activation function [26]. This network inte-grated a more efficient convo-lution mechanism with an innovative architectur-al de-sign, resulting in a reduced model size while maintaining high detection performance.

In addition, the dynamic CNN model DCN_Fire [27] was developed for evaluat-ing the risk of forest fires. It employed principal component analysis (PCA) transfor-mation methods to im-prove inter-class discriminability and incorpo-rated saliency de-tection to segment flame images into uniform sizes for training the model. Experi-mental results showed that DCN_Fire achieved an accuracy of 98.3% on the test da-taset.

A CNN model with an attention mechanism for fire detection employing GRAD-CAM visualiza-tion to illustrate the contribution distribution of the model's flame predictions [23]. These diverse ap-proaches highlight ongoing efforts to enhance the effective-ness of fire-detection models through in-novative network architectures and methodologies.

Convolutional neural networks (CNNs), re-current neural networks (RNNs), and their vari-ous iterations have become foundational tools for the construction of com-prehensive end-to-end fire-detection systems. The continuous advance-ment of deep learning models is a key area of focus, with researchers continually investigating new adaptations tailored to particular image characteristics. This ongoing exploration significantly contributes to advancing the field of fire detection, highlighting the dynamic nature of development in response to evolving technological landscapes. The iterative progression of these advancements underscores the unwavering commitment of the scientific community to consistently enhance the efficacy and applicability of fire-detection systems. This dedication reinforces their main role in safeguarding against environmental threats, emphasizing the importance of adaptive and innovative approaches in the realm of fire detection.

METRICS FOR FIRE RECOGNITION

The effectiveness of neural networks in the detection of threats, specifically in fire recognition, is assessed using various metrics. In multi-classification scenarios, metrics such as true positives TPs (correctly identified fires), false positives FPs (instances mistakenly identified as fires), true negatives TNs (correctly identified non-fires), and false negatives FNs (non-fires mistakenly identified) play a main role. They are used in the Equations 1–5. Typical evaluation metrics are: accuracy rate (AR), detection rate (DR), precision rate (PR), false alarm rate (FAR), and false negative rate (FNR) [30].

The Accuracy Rate (1) measures how often the model correctly identifies both positive and negative samples in fire-detection tasks. It provides an assessment of the model's recognition performance and is a key indicator of the algorithm's effectiveness.

$$AR = (TPs + TNs)/(TPs + TNs + FPs + FNs) \times 100\% \quad (1)$$

The detection rate (2) shows how well the algorithm accurately identifies all fire samples as fires.

$$DR = TPs/(TPs + FNs) \times 100\% \quad (2)$$

Precision Rate (3) is the percentage of correctly identified fires out of all the samples marked as fires.

$$PR = TPs/(TPs + FPs) \times 100\% \quad (3)$$

False Alarm Rate (4) and False Negative Rate (5) are essential in fire detection. The False Alarm Rate (FAR) shows how often non-fire things are mistakenly thought to be fires, while the False Negative Rate (FNR) reveals how often fires are missed.

$$FAR = FPs/(FPs + TNs) \times 100\% \quad (4)$$

$$FNR = FNs/(FPs + TNs) \times 100\% \quad (5)$$

The F-measure approach (6) is a widely used metric that merges the Detection Rate (DR) and Precision Rate (PR), acting as the harmonic mean between these two measures. A higher F-measure, approaching 1 (7), signifies enhanced accuracy, providing a useful means to assess the algorithm's strengths and weaknesses effectively. The parameter β in $F\beta$ (signifies the degree of bias toward either the Precision Rate or Detection Rate during the algorithm evaluation.

$$F_{\beta} = (1 + \beta\text{^}2) \times PR \times DR)/ /(\beta\text{^}2 \times PR + DR) \times 100\% \quad (6)$$

$$F_1 = (2 \times PR \times DR)/(PR + DR) \times 100\% \quad (7)$$

Taking into consideration a available dataset, the evaluation of CNN performance for fire detection models was conducted to verify it usefulness in diverse environmental conditions. The fire detection model is based on convolutional neural network (CNN) trained on a dataset comprising aerial and ground-based wildfire images. The dataset sources include:

- publicly available wildfire datasets: FLAME and FireNet;
- synthetic data augmentation techniques, considering smoke overlays, varying illumination conditions, and background clutter simulations.

For model training, a YOLOv5-based CNN was selected due to its efficiency in real-time object detection and adaptability to dynamic fire propagation patterns. The training was conducted over 50 epochs using the Adam optimizer, with a learning rate of 0.001 and a batch size of 32, leveraging an NVIDIA GPU-based computing environment to accelerate processing. To improve the model's robustness to environmental variations, data augmentation techniques were implemented, including:

- random rotations and flips,
- gaussian noise simulating distortions in UAV-acquired images,
- contrast variations related to low-visibility nighttime scenarios.

The initial results (Figure 13) demonstrate the potential usefulness of AI models in supporting

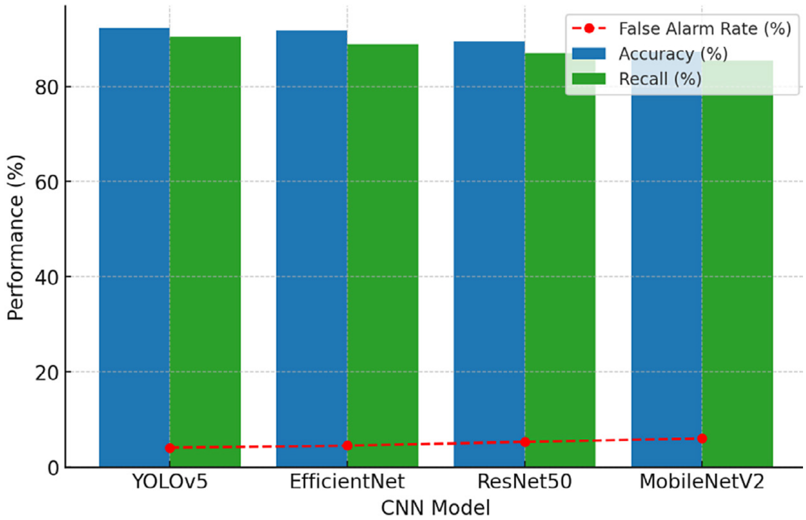

Figure 13. Comparison of fire detection CNN models

wildfire monitoring, improving the reliability of UAV-based reconnaissance missions in high-risk ecosystems. The comparison of fire detection CNN models, showing their accuracy, recall, and false alarm rate. The results suggest that YOLOv5 performs best, achieving 92.3% ac-curacy and the lowest false alarm rate (4.1%), making it a strong candidate for re-al-time wildfire detection.

The preliminary results indicate that the CNN model's capability to process aerial and thermal imagery is suitable for fire detection, even in challenging environmental conditions such as low visibility, dense smoke, and varying illumination. The integra-tion of multi-spectral data allows for better differentiation between actual fire hazards and false positives, contributing to a more reliable fire detection framework for UAV-based reconnaissance missions. Despite these promising outcomes, further improvements are essential to increase model robustness across diverse terrains and weather conditions. Variations in at-mospheric conditions, terrain features, and seasonal changes may impact detection accuracy, requiring the adaptation of AI models to dynamic environmental factors.

Future research will focus on expanding the dataset with real-world related to scenarios similar to Biebrza National Park as well as fire incidents to improve gener-alization, optimizing sensor fusion techniques by integrating thermal, RGB, and Li-DAR data, and refining AI-driven UAV-UGV collaboration for enhanced autonomous wildfire monitoring and response. These advancements aim to develop a more resilient and adaptive system for real-time fire detection and risk assessment in high-risk eco-systems

CONCLUSIONS

This research describes the collaborative deployment of a UGV and UAV for reconnaissance missions within Biebrza National Park. The proposed integration offers a novel and multifaceted solution, combining the strengths of autonomous ground-based and aerial platforms with advanced AI capabilities.

UGVs, equipped with sophisticated sensors and cameras, are capable of navigating challenging terrains with precision, providing real-time observations and data collection. Their ability to traverse areas that may be difficult for human patrols makes them invaluable for surveillance and threat detection in expansive and intricate landscapes like Biebrza National Park.

Simultaneously, UAVs contribute to aerial reconnaissance, covering vast areas efficiently and swiftly identifying potential threats such as fire hazards or illegal activities. Equipped with advanced sensors, these aerial platforms provide real-time environmental data, aiding in the early detection of potential risks and facilitating rapid response strategies. The integration of remote sensing technologies further augments this comprehensive safety framework. These technologies enable the acquisition of valuable data related to environmental conditions, vegetation health, and potential fire-prone areas. The study emphasizes the role of vehicle contact pressure analysis for determining where UGVs can safely operate in swampy or ecologically sensitive terrains and where UAV deployment is more suitable, particularly for rescue or emergency missions.

The initial version of this study provides a comprehensive overview of scenarios in which the proposed system can be applied, along with an analysis of peat bog fire threat detection. It highlights the importance of precise, efficient, and early wildfire detection and demonstrates how modern vision systems and deep learning methods can significantly outperform conventional approaches in specific scenarios. This paper thus contributes valuable insights into integrating robotics, remote sensing, and deep learning for advanced reconnaissance and wildfire monitoring in challenging environments. The operational performance of the proposed system is influenced by environmental factors such as weather variability, vegetation density, and the presence of water bodies. These conditions affect UAV flight stability, AI-based fire detection reliability, and communication network quality. Addressing these challenges in future research will require environmental modeling, multi-modal sensor fusion, and adaptive communication strategies to enhance resilience under diverse conditions.

This study is conceptual as a preliminary framework to support an application for national or international research funding exclusively for system components development and deep investigation. The final project will be carried out with the involve-ment of Poznan University of Technology, which has contributed to the development of the UAV platform described in this study. Their expertise in this field plays a crucial role in advancing the proposed system toward real-world application. Future work will involve implementing the proposed system in simulation environments, validat-ing UAV-UGV communication and task planning strategies, and applying AI methods for adaptive decision-making in complex environments.

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