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Integrating Data Mining Methods into Smart Drone Systems for Supporting Visually Impaired Users

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Research Article

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Abstract

Uncertain outdoor travel in dynamic environments continues to be a problem experienced by the visually impaired. While existing assistive technologies offer valuable assistance, much of it is distance-based and may issue alerts which are too late or lack clarity. In this paper, we propose an augmented information system that integrates smart drone sensing and data-driven analysis for enhanced navigation support outside. A small unmanned aerial vehicle acquires visual, depth, and/or positioning data and transmits the captured data to a processing unit located at an edge. From there, the data are processed and analyzed through methods of clustering, classification, and anomaly detection to learn possible dangerous experiences as well as paths in which safe movements occur. The collected data is presented in a non-intrusive way through brief audio and haptic outputs that minimize cognitive effort. The results of the scenario based simulations demonstrate that compared with the traditional Sensor mounted in ground level, (1) the proposed system is able to recognize outdoor obstacles efficiently; (2) has a better response behavior and (3) yields fewer false warnings. The research provides an information systems perspective on drone assisted navigation, emphasizing the importance of governance, privacy-awareness design and explainability, towards trustworthy decision-support solutions.

Highlights

• Demonstrates an information tool that connects drone-based sensing with data analysis for assisting outdoor mobility.

• Real-time analysis flow for clustering, classification and anomaly detection to evaluate navigation risk.

• Demonstrates better obstacle detection performance with improved false positive rates compared to a traditional ground-based method.

• Includes governance mechanisms such as privacy constraints, activity logging and explainability to enhance the accountability of the system.

• Provides design recommendations for development of an inclusive and robust decision support in safety-critical assistive applications.

1. Introduction

IS have come to constitute the debate around people's understanding of, and behaviour in complex environments. " Blind pedestrian access to timely and clear information about surrounding hazards, walkable space, available movement options is essential in order to navigate independently. Traditional mobility aids such as the white cane and guide dog are still highly effective in many situations; however, they are fundamentally constrained to close-range direct physical interaction. These tools therefore offer little early warning of dynamic circumstances. Thus, more recent works in this direction have

investigated the application of digital travel aids built on top of wearable technology and computer vision. Nevertheless, in cluttered outdoor environments where occlusion, dense pedestrian activity and unpredictable motion are present, many of these systems degrade their performance1.

A different sensing point of view can be searched for thanks to smart drones that, from the above, are able to detect obstacles and movement (dance-like) patterns. Nevertheless, UAV platforms produce heterogeneous data streams that are not useful for navigation without proper processing. The use of data mining such as clustering, classification, and anomaly detection provides a practical means of extracting patterns that are pertinent to these phenomena from the large amounts of data available and converting them into actionable knowledge for decision support [2,3]. From an IS perspective, the issue of concern is not only that of accurate perception, but also pertains to whether the information delivered is reliable; transparent; and subject to governance, control and trust within systems that are operating under safety-critical work scenarios [4,5].

In this context, the research explores: “How smart drone technologies supported with data mining techniques can be employed to assist visually impaired users in an assistance system?” The paper presents four types of contributions: (i) a layered architecture of IS for drone-assisted navigation; (ii) an analytics pipeline interconnecting perception with risk assessment and alert prioritization pathways; (iii) scenario-based evaluation approach, available in on-going European Research Project project DREAMS 4.0 as well as a testbed to evaluate the above-mentioned architecture and design pipelines; and (iv) placing privacy protection, accountability, and explainability at the fore-front of system design implications.

2. Background and Related Work

Assistive navigation has been addressed by a number of works, including assistive devices for people with visual impairments, vision-based smartphone applications and infrastructure-supported systems. Previous review studies often discuss a trade-off between how far the system can sense, how trustworthy the system can be and how much mental activity is needed from the user. the relationship between them can be described by the following utility function::

$$U = \alpha R + \beta \rho - \gamma L \quad (1)$$

where R, ρ and L are sensing range, reliability and cognitive load [1], respectively. Although vision-based approaches can offer precise scene information, they tend to perform poorly in practical outdoor conditions. For instance, poor lighting, camera movement and occlusion hinder the correct recognition chance (see Fig. 1.) as reported in [6].

UAVs have been studied as a method of increasing situation awareness, and guidance using auditory and haptic feedback. Experimental evidence indicates that people are able to effectively move behind a drone as visual or directional reference, if interaction rules and safety limits are properly enforced [7–9].

For a navigation safety perspective, guidance can be characterized by imposing the minimum permissible distance between the user and obstacles.

$$d(t) \geq d_{min}, \quad (2)$$

whilst maintaining a movement within a predetermined safe trajectory. This constraint is illustrated in Fig. 2., which depicts situational awareness at a road convergent point.

When information systems deal with data that represent some aspect of the human context, concerns about responsible use, transparency, supervision are exceedingly crucial [4,5,10]. These worries are the ones that drive practical limits to data retention time and where computation is done. Studies on real-time UAV based analytics also confirm that processing is often offloaded to the edge, and lightweight analytical models are preferred due to tight time deadlines and limited energy capacity [11,12]. Therefore, the system behavior also has to be kept within some bounded end-to-end response time.

$$T_{e2e} \leq T_{max} \quad (3)$$

At the same time, energy consumption on the drone needs to remain in the realm of practicality. This restriction promotes on-device data processing/analysis as opposed to overpowering cloud-based computations. Within this context, UAVs have been addressed as devices to enhance situational awareness and to assist navigation with audio and haptic cues. An example for this design is illustrated in Fig. 3.

Preliminary studies indicate that users can navigate by tracking a lead drone as long as safety boundaries and interaction design parameters are adhered to [7–9]. In parallel, studies in information systems highlight how systems process sensitive and context-dependent personal human data, underscoring the requirements for transparent governance [4], [5], [10]. Similarly, the study of real-time UAV analytics also remarks that the power and processing constraints demand edge-based light-weighted calculations, as opposed to computationally expensive techniques [11,12].

3. Research Model and System Architecture

The system is divided into functional layers as illustrated in Fig. 4. The UAV collects sensor information from its local area and forwards them to an edge entity, which can be hosted either on a drone or in a tethered smartphone. This member computes the data and provides feedback about the navigation to the user. In support of responsible operation, the system is designed with a governance layer that controls privacy settings, logs system activity and provides minimal explanations for system decisions to build trust and accountability [4,5].

The main data mining components and their corresponding decision-support outputs are summarized in Table 1.

Table 1
Components of the data mining and outputs.

Mining component	Operational role	Decision-support output
Clustering	Partition local scene into free space and obstacle regions	Traversable corridor + confidence
Classification	Label obstacle type (pedestrian/vehicle/static) under edge constraints	Semantic label + distance
Anomaly detection	Flag unusual motion or unexpected hazards	Priority alert + risk score

4. Methods

The system should be robust enough to support outdoor movement on sidewalks and crossing pedestrian crossings. The color images and depth data are obtained by the UAV, while its position and orientation are provided by GPS/inertial sensors. Received data are first temporally aligned and then filtered for noise. Thereby basic features are derived, such as the location and distance of objects, their moving speed, and estimates of available walking space. These characteristics are dealt with as continuous flows so that the analysis can be done with a low latency.

4.1 Clustering for identifying walkable areas

Clustering then groups depth points that are closeby and opens up walking areas from cluttered/surrounding regions. To avoid spurious guidance, the clustering results are combined with evidence of sensor quality (i.e. depth measurements fluctuations when strong ambient environment occurred, as problematic situation).

4.2 Classification for environmental awareness

A lightweight classification model is used to locate common scene elements, e.g. pedestrians, vehicles and fixed objects. By using such labels, the system can produce more explicit guidance messages (e.g. separating into static and moving obstacles) resulting in less confusion compared to generic alerts [6].

4.3 Anomaly detection for risk handling

Anomaly detection is concerned with separation of the unusual motion behavior (or an unexpected trajectory change). Instances where objects are moving in and out very quickly (like people crossing the street with their cellphones) or there's a sudden change in pedestrian flow are considered higher risk. Events are detected in a hierarchical manner so that important warnings are presented sooner than unimportant ones to prevent unnecessary disturbance to the user and cognitive effort. The evaluation scenarios considered in this study, along with their primary hazards, are summarized in Table 2.

Table 2
Evaluation scenarios and primary hazards.

Scenario	Description	Primary hazards
S1 Routine	Sidewalk with poles, curbs, signs	Static obstacles; narrow passages
S2 Accidental entry	Pedestrians intermittently enter corridor	Near-collisions; occlusions
S3 Vehicle approach	Crossing with approaching vehicles	Fast objects; speed estimation
S4 Coordinated hazards	Multiple agents + sudden blockage	Compound risks; alert prioritization

5. Results

Performance of the system is evaluated based on three features: correctness of obstacle detection, false warning ratio and reaction time. Our results are compared with the ground-based reference approach where short-range sensing is used, and alert rules are predefined according to classifications often seen in assistive navigation literature [1] Fig. 5. compares the overall performance of the proposed UAV-based system with the ground-based baseline in terms of detection accuracy, false alerts, and response time.

As shown in Fig. 6., the end-to-end latency increases with scenario complexity, while remaining within acceptable response-time limits.

Aggregate performance results across all scenarios are reported in Table 3.

Table 3
Aggregate performance across scenarios (mean values).

Metric	Ground-based baseline	Proposed UAV + data mining
Obstacle detection accuracy (%)	78.5	91.2
False alert rate (%)	15.3	6.4
Average response time (s)	1.8	1.1

In all scenarios studied the aerial sensing can let the user know about an obstacle sooner, than are not directly in his close range. Meanwhile, the data processing pipeline refines warnings by rejecting ambiguous signals and concentrating on higher-risk events. We are able to achieve good class-wise separation among the primary scene classes under normal conditions This behavior is reflected in the normalized confusion matrix shown in Fig. 7., which indicates good class-wise separation under normal conditions for being more context-sensitive.

6. Discussion

The results suggest that the integration of drone-based sensing and data-driven analysis may accelerate delivery and enhance reliability of mobility help. From an information systems entity POV, the value of such a system is critically dependent on the quality of the available information, especially in terms of accuracy, reliability and timelyness - within cognitive and safety limits. The governance factor becomes critical due to the fact that in using drones we inevitably capture nearby individuals, which can be controlled partially by restricting data collection and embedding privacy-by-design, ultimately treating ethical and regulatory implications (cf. [4,5,10]).

Several challenges remain in practice. Battery size restrictions the operation period, regulatory guidelines can prevent deployment in populated areas and user acceptance is to a large extend connected with perceived comfort and safety. Future research should therefore have its focus on real life testing with user's centered UI design and investigate how clear, understandable risk information affects trust and continued use.

7. Implications for IS Research and Practice

From a research point of view, this work demonstrates how drone based sensing can be considered as a decision-support information system that accommodating real-time data processing, analytical operations and user orientated interaction. In the real world, the presented architecture provides a roadmap for developing assistive systems that focus on actionable rather than raw sensor data with explicit consideration of privacy by design and also system accountability.

8. Conclusion

This study developed an assistive information system with smart drones and data-driven methods to support navigation of visually impaired people. Clustering, classification, and anomaly detection of aerial sensor data are performed in order to produce guidance based on risk as it is disseminated via audio and haptic notifications. Simulations demonstrate superior obstacle detection, less unnecessary warnings and faster reaction times with respect to a terrestrial reference system. They will continue to advance efforts to evaluate in real-world settings, and to personalize the tool for individual users, as well as to create governance structures that would foster broader safe and responsible use.

Declarations

Ethics Statement

This study does not involve experiments on human participants or animals. The work is based on system design, simulation, and scenario-based evaluation. No personal or identifiable data were collected, stored, or processed. Therefore, formal ethical approval was not required.

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Declaration of competing interest

The authors have no conflicts of interest to report concerning the work in this paper.

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Figures

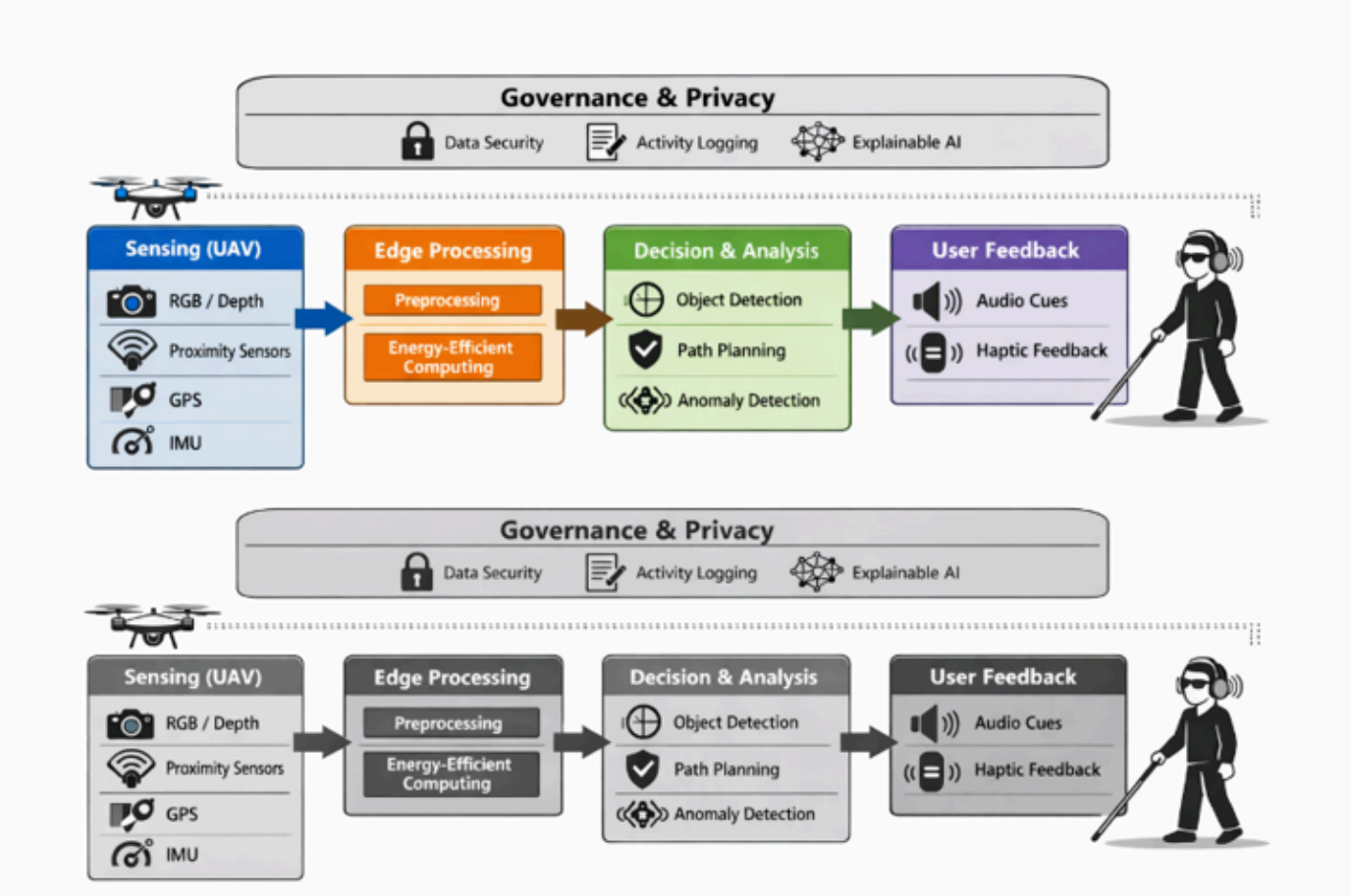


Figure 1

illustrates the overall data flow architecture of the proposed smart drone–based assistive navigation system.

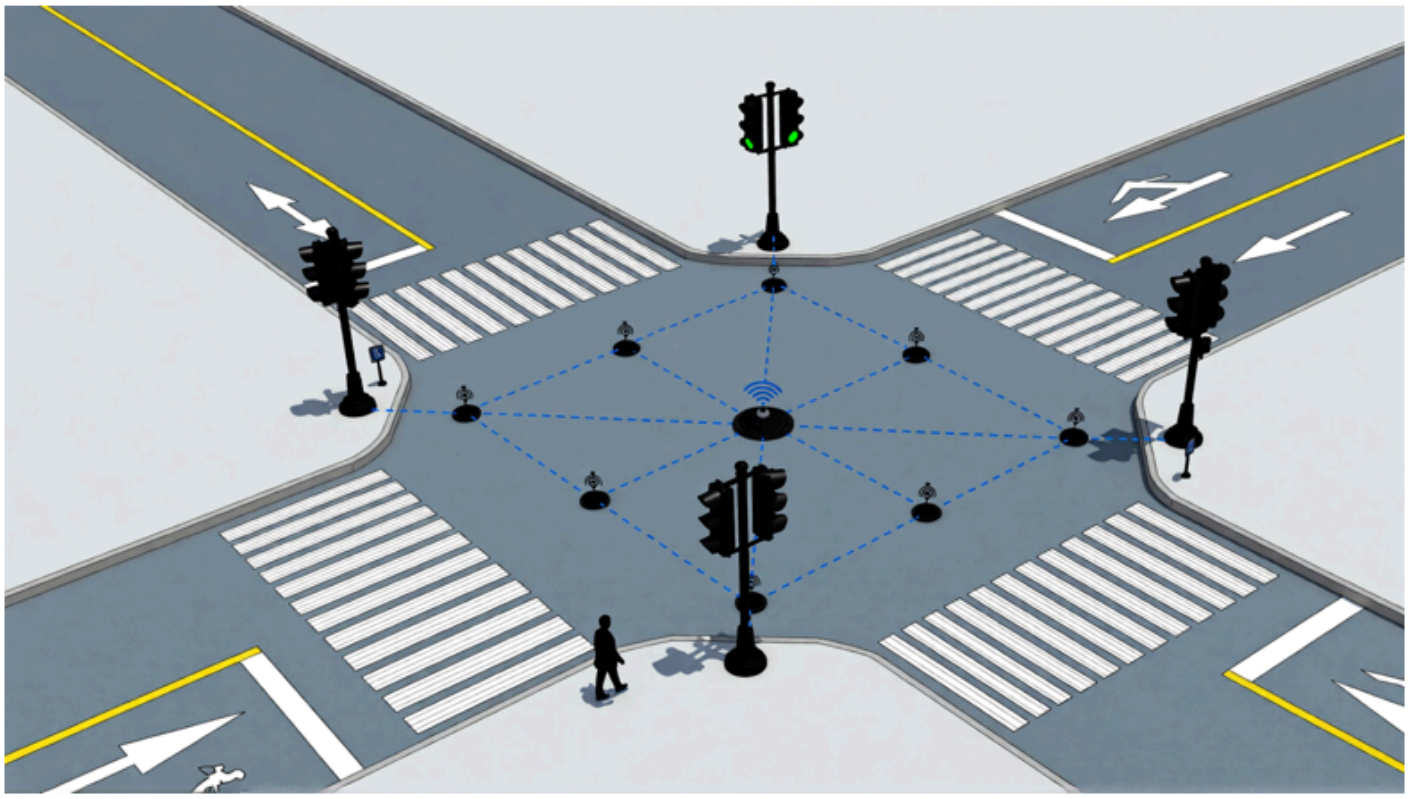


Figure 2

Situational awareness at a road convergent point with UAV.

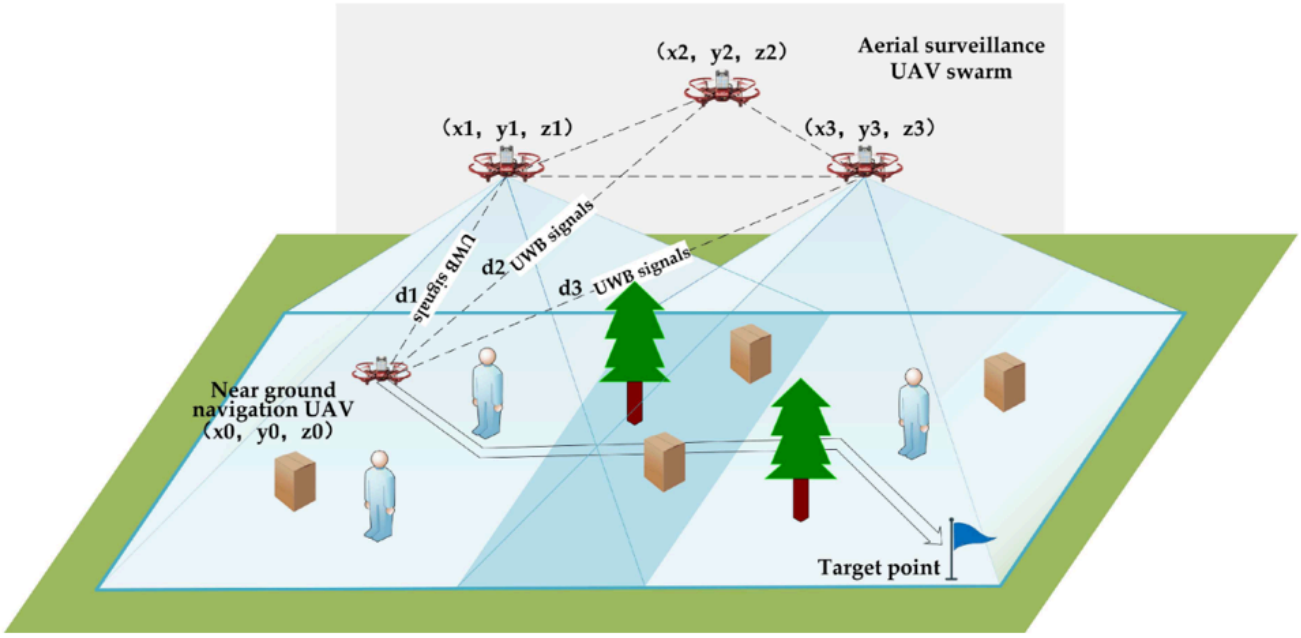


Figure 3

illustrates the task offloading and edge-assisted data processing model adopted by the system.

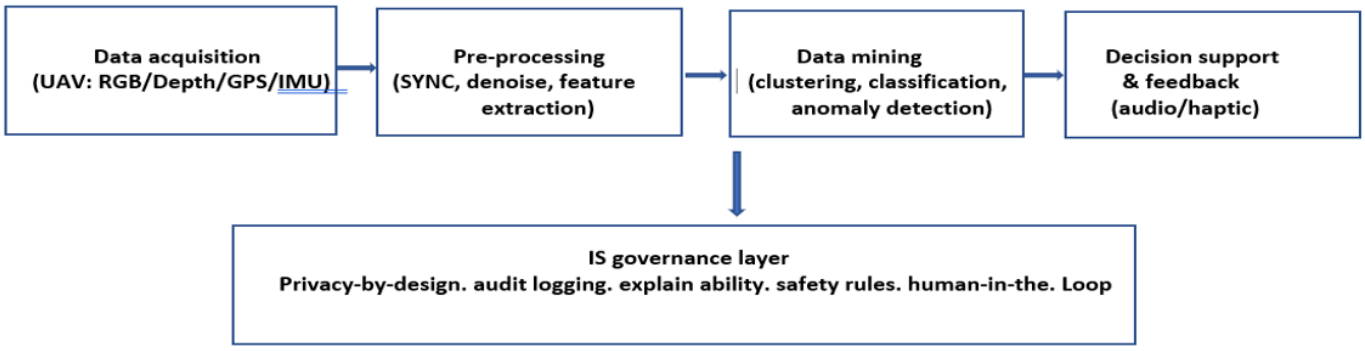


Figure 4

The architecture of the assistive information system based on UAV.

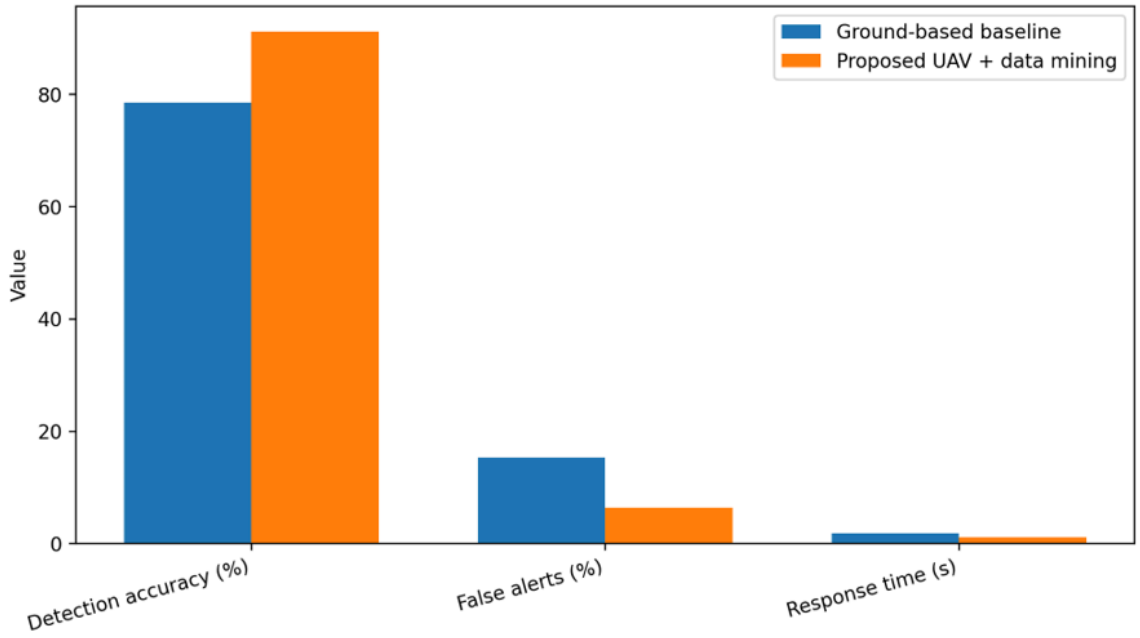


Figure 5

Overall performance comparison between the ground-based baseline and the proposed UAV + data mining system.

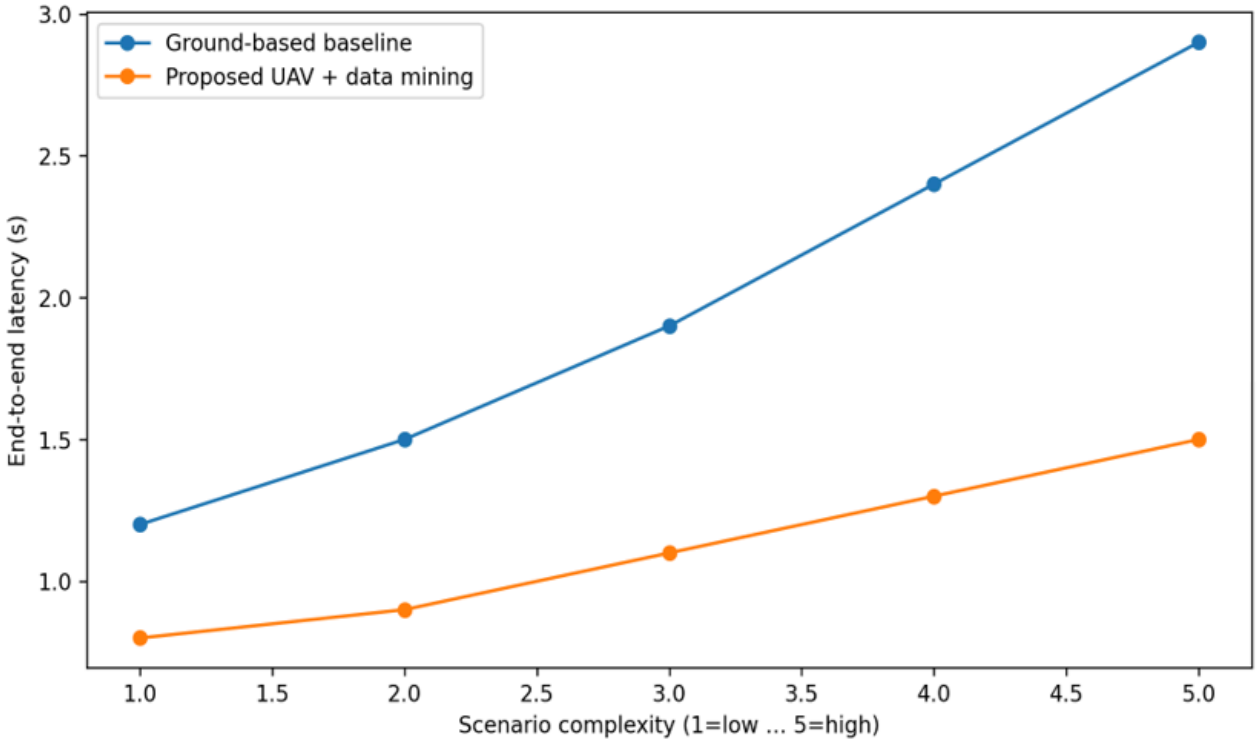


Figure 6

End-to-end latency versus scenario complexity (higher complexity implies more obstacles and moving agents).

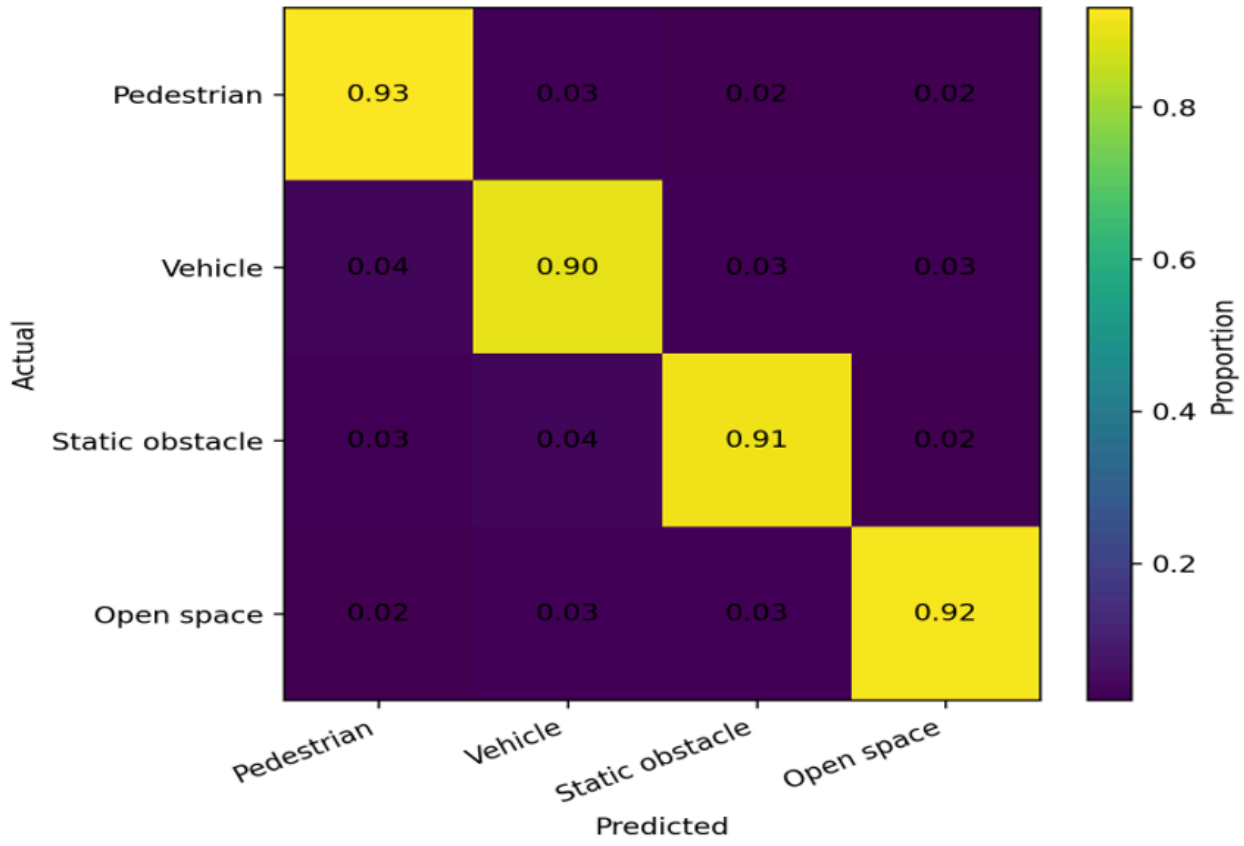


Figure 7

Classification performance (normalized confusion matrix) for four scene classes (synthetic illustration).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryMaterialCode1.docx
- SupplementaryResults.docx
- SupplementaryTables.docx