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ENHANCING INFORMATION RESOURCES FOR URBAN FREIGHT MANAGEMENT THROUGH IMAGE PROCESSING AND ANALYSIS

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The issue of incomplete data on the volume and types of freight transport in urban areas is well known, leading to difficulties in managing transport processes and hindering the development of strategic approaches for modern cities. To improve the management of freight flows, it is essential to distinguish freight vehicles from private and public transport. This paper investigates and develops methods for vehicle detection and tracking using cameras mounted on unmanned aerial vehicles (UAVs), aiming to enhance urban logistics data through image processing and analysis algorithms. A multi-camera vehicle detection and tracking algorithm was developed to support the analysis and evaluation of traffic flow efficiency in urban logistics, ultimately contributing to improved transportation management aligned with emission reduction principles.

Keywords: Urban freight transport, city logistics, sustainable urban mobility plan, data driven logistics, intelligent transportation system, emmerging technologies, image processing

1. Introduction

The contemporary challenges of transport require a global, innovative vision of urban development. Real-time traffic management systems capable of handling traffic congestion rely on strategies and adaptive control. The adopted models for selecting routes and logistic activities are based on heterogeneous data obtained from many, often diverse sources, with undeniable impact on the development of urban areas. Research into logistics efficiency, sustainable freight transport and carbon dioxide emissions optimisation shows the complexity of these processes. Public initiatives and development models for urban freight transport systems promote equality, equity and sustainable mobility.

In the context of dynamically developing urban agglomerations, it is necessary to choose comprehensive, integrated transport strategies. Innovative technologies such as big data, machine learning and the Internet of Things (IoT) support these strategies by using devices such as cameras, sensors, induction loops and unmanned aerial vehicles (UAVs, commonly referred to as "drones") to collect, process and share data, which have evolved to the rank of key end devices in the IoT. Combining these technologies can provide significant benefits to urban transport, for example, by directly estimating goods flows or traffic models optimisation. The main hypothesis is formulated as follows: "The application of drone grids for video data acquisition and utilisation of automatic image processing algorithms to generate useful information will enhance the information resources of urban logistics systems."

This paper presents the concept of implementing a user-independent data acquisition system for traffic and routes analysis within a city, as well as an indication of the technological assumptions and requirements for the system of utilising unmanned aerial vehicles to analyse traffic flows. Acquisition, collection and processing of video data from drones, requires a structured approach to automatic identification of objects in motion from multiple cameras simultaneously. The primary goal of this paper is to develop an algorithm for vehicles identification in urban traffic using those cameras. The secondary goal is to obtain additional data on urban freight transport traffic streams that will help supplement the information resources and close data gaps in the planning and design processes of urban logistics.

2. Literature review

The subject literature includes a significant number of studies on acquisition and analysis of data from various sources and on technologies that enable it. In their papers, the authors focused on developing effective solutions, but also on identifying areas requiring further research. The studies cover a wide range of topics, including data collection methods, data analysis algorithms, and the use of modern technologies

such as artificial intelligence, machine learning, and big data analytics. The researchers aimed to create frameworks that enhance efficiency and accuracy of data processing, which is crucial for various applications.

In the context of freight transport in cities, the literature highlights several contemporary solutions aimed at supporting these processes. These include development of smart logistics systems, application of the Internet of Things (IoT) to monitor and manage freight movement, effective collection and analysis of data supporting logistic or operational processes and the use of predictive analytics to anticipate demand and optimise routes. Table 1 presents a selection of the literature concerning issues related to the analysis of freight transport in cities. It includes studies that address the challenges of urban logistics, such as traffic congestion, dynamic route planning, environmental impact, and the need for efficient delivery systems.

Table 1. Literature review of emerging technologies in intelligent transportation systems

Paper	Scope	Data source/type	Research focus and main findings
(Li et al., 2023)	Logistics, UAV	Own study, UAV data, opensource maps	A logistics UAV route planning approach proposal for urban areas.
(Belfadel et al., 2023)	Logistics, framework scenario	City operational data, MATSim and Visum data, case scenarios	A systematic review of the literature, proposing a conceptual framework for digital twin applications in urban logistics.
(Pegado-Bardayo et al., 2023)	Decision-making, Route prediction,	Couriers service data, GIS data, weather conditions	A data-driven decision support system for service completion prediction in last mile logistics.
(Li et al., 2024)	Traffic, traffic control models	Roadside camera sensors, traffic behaviour data, trajectory data	Predictive system aimed at estimating the propagation of multiple traffic congestions. Proposal of strategies, enabling adaptive and automatic selection of traffic control modes.
(Song et al., 2024)	Transport, data-driven framework	Cellular data, mobile trajectory data, traffic data, GPS trajectory dataset	Travel choices behaviour model based on inverse reinforcement learning. Decision-making, and potential transportation system vulnerabilities.
(Quttoum, 2022)	Transportation, routing model	User's charging behaviour, route points	Autonomous adaptive routing model providing navigation scheme for shortest routes with least computing times.
(Kiba-Janiak et al., 2021)	Transportation	Survey, data from capital cities	An integrated approach to passenger and freight sustainable transport strategy. City's maturity level.
(Khan et al., 2017)	UAV studies, Traffic	Existing studies, literature data	A strategy framework for ensuring UAV-based traffic study.
(Nadi et al., 2024)	Transportation	Netherlands Central Bureau for Statistics	Routing and scheduling model for activity-based freight transport modelling. Estimation method proposal for operational research and machine learning techniques.
(Katsela et al., 2022)	Sustainability	Own study, sample cases	Analysis of issues concerning urban freight sustainability and efficiency improvement.
(Y. Wang et al., 2020)	ITS, Vehicle identification,	VehicleID and CCTV datasets	A detection algorithm which reduces the error rate of identification
(Iwan, Jedlinski, et al., 2023)	Urban freight transport	Own study, literature review	Knowledge management, freight traffic.
(Abadia & Smarsly, 2023)	IoT, Smart Cities	Systematic review	Review of the various IoT elements and technologies utilized in IoT frameworks for smart city applications
(Iwan, Wagner, et al., 2023)	Urban freight transport	Questionnaire survey	Knowledge-based city logistics; data sharing and ownership; mobility knowledge management;
(Bashir et al., 2022)	Traffic surveillance	Own study, Wireless Sensor Network and UAV	System architecture for traffic surveillance effectiveness increases with varying traffic patterns.
(Evangeline et al., 2023)	ITS, UAV, blockchain	Own study	A blockchain based secure transmission between UAV and vehicle for smart city environment
(Salazar-Cabrera et al., 2019)	UAV, management, smart city	Own study. Use case scenario	Development of a supervisory control and data acquisition system for inventory management
(Wen and Wu, 2022)	Drone routing problem	Own study, Baidu Maps	Two-echelon routing, Heterogeneous drones, Parcel delivery
(Kumar et al., 2022)	Traffic monitoring, drones.	Drone communication	Drone-to-drone communication, software defined drone enabled traffic monitoring system.
(Liu and Bai, 2023)	Traffic monitoring, droness.	Own study, Drone communication	Collaborative traffic monitoring. UAVs as ground monitoring equipment.

Continuation of Table 1

Paper	Scope	Data source/type	Research focus and main findings
(Javaid et al., 2023)	Drone-to-drone communicat.	Review. Use case scenario	Characteristics of UAVs communication and control requirements.
(Shankaranarayan and Kamath Sowmya, 2022)	Smart traffic systems, urban surveillance, computer vision	Review. Design and validation datasets	The use of image processing techniques to monitor vehicle traffic in cities, aiding in route optimization and congestion reduction
(He et al., 2016)	DNN, image recognition	ImageNet dataset	Deep learning for image recognition
(Katrakazas et al., 2021)	Traffic conflicts, safety	Inductive loop detectors	Rear-end conflict frequency in an urban network, data modelling
(Saleem et al., 2022)	CV, ITS, vehicle detection	Review article	A comprehensive review of the various techniques available for video-based traffic surveillance from a computer vision data
(Aloui et al., 2021)	Sustainability, logistics	Review article	Literature review for sustainability and collaboration in transport
(Binjaku et al., 2023)	Traffic control, ML	Real time data from Performance Measurement Systems	Hybrid modelling framework in which a Machine Learning model controls traffic and passenger behaviour
(Otto et al., 2018)	UAV traffic monitoring	Survey of available technologies	Optimization approaches for civil applications of unmanned aerial vehicles
(Bozzi et al., n.d.; Čičić et al., 2022)	Truck platoon traffic control	Real time data	Tracking model of platoons presence on, modelling, traffic measurements

The literature covers various elements of the urban cargo distribution process, from representation of the last mile supply chain, through computer simulations of traffic users' behaviour and interactions, to ICT technologies used to analyse traffic flows and behaviours of traffic participants. The analysis indicates that most articles focus on the issue of gathering appropriate data, technologies and techniques of image processing, pattern recognition, image segmentation, and motion analysis, methods that allow extraction of essential information from images, which can significantly enhance the information resources used in city management. However, discussions on the use of UAVs in transport focus mainly on their flight routes optimisation, while ignoring the potential of images obtained from drones (especially from multiple drones) as an additional source of decision-making data. There is a noticeable lack of literature addressing this particular issue. Utilising drones as data collection devices, is a good way to obtain up-to-date information on road conditions, congestion, and the behaviour of drivers and pedestrians. For this reason, the authors stated that a multidimensional approach to data acquisition from drones presents new opportunities for modern transport. Hence, the aim of this article is to show their potential.

2.1. Data-driven logistics modelling

City authorities are responsible for urban logistics functioning and fulfil this obligation by developing and implementing transport policies. In accordance with accepted good practices, city authorities should develop a Sustainable Urban Mobility Plan in relation to the problem of mobility and transport within the city. It should be emphasised that an important part of SUMP is the Sustainable Urban Logistics Plans (SULP), which is a plan dedicated to freight transport. Some experts believe that due to the fundamental differences in the transport of people and cargoes, the authorities should develop two separate SUMP and SULP documents (Foltyński, 2016), (Iwan *et al.*, 2023), Kiba-Janiak and Witkowski, 2019), (Rupprecht *et al*., 2019), (Taniguchi *et al.*, 2001). In addition to many different types (sizes) of delivery vehicles (electric and traditional), urban logistics tasks can also include other vehicles, such as city bikes (electric and traditional) and all types of electric vehicles, such as scooters and tricycles. Due to the fact that, according to the authors' concept, traffic flows consisting of means of transport of both people and goods are subject to analysis, it should be noted that the acquired data can be used in the process of creating both SUMP and SULP documents. It is important that the proposed algorithm allows classification of vehicles, among other things, in terms of their purpose, so it's a universal tool.

2.2. City logistics data collection processes and systems

Many devices are used to acquire and collect data from within and outside cities to model traffic flows for short- and long-term analysis and planning. For this purpose, various technical means are used, involving many different, often heterogeneous solutions, such as induction loops, vibration and

vibroacoustic sensors, infrared sensors, optical motion sensors, stationary video cameras, ANPR cameras, LIDAR technology and others (Boukerche *et al*., 2017), (Bugdol *et al*., 2014), (Chen and Liu, 2021), (Dickinson and Waterfall, 1984), (Leduc, 2008), (Małecki and Iwan, 2019), (Nowosielski *et al*., 2020), Pamula, 2009), (Sun *et al*., 2006). Despite a wide range of possibilities for traffic detection and vehicle classification, there is a gap in access to detailed data from traffic flows generated by vehicles used in urban logistics. Courier companies transporting goods do not provide data on the number of deliveries performed, their area of operation, or the number and types of vehicles used for this purpose. Lack of data and knowledge about this process constitutes a barrier for local, regional and national authorities involved in road maintenance and sustain-able transport planning to reduce harmful emissions, gases and noise in cities. To improve the planning of new, and optimise existing urban infrastructure investments, it is necessary to expand the existing vehicle classification methods to include modern technologies based on multi-camera vision systems.

Acquisition of traffic parameters, such as vehicle speed, vehicle type classification and the like, can be improved using UAV-mounted vision devices. UAVs can perform flight operations in places where manned aviation cannot be used (dense urban infrastructure), and their use brings significant economic and environmental benefits with minimal risk to people. UAV traffic testing methods, unlike other methods, are non-invasive, environmentally friendly and ready for use in dynamically changing circumstances.

3. Materials and methods

In recent years, there has been a significant increase in the popularity of CCTV cameras. It is related to the availability of the overall availability of CCTV cameras installed in cities at road intersections and other critical points (roundabouts, parking lots, expressways, etc.). Surveillance of highways, tunnels and city streets is on the increase. However, it should be noted that cameras are mainly used for passive observation and recording of traffic incidents, and rarely as sensors for data acquisition. The spatial characteristics of traffic are forcing the development of new methods of traffic control and an increased interest in the use of video cameras covering larger operational areas. Since the early 1980s, scientific publications have been developing methods and tools for the automatic analysis of traffic images (Bommes *et al*., 2016), (Bouguet, 1999), (Canny, 1986), (Chen and Chen, 2006), (Dickinson and Waterfall, 1984), (Lucas and Kanade, 1981), (Nourani-vatani *et al.,* 2006), (Pamuła, 2014), (Regazzoni *et al.,* 1999), (Wigan and Cullinan, 1984). However, these methods require constant updating and adaptation to dynamically changing road conditions. Such assumptions are met by the system described in this article for using a drone grid to collect video data and analyse vehicle traffic streams.

The main tasks in the field of computer vision include automatic identification of computer systems. Researchers aim to develop algorithms for automatic perception, such as object recognition (Ammour *et al.,* 2017), (Chang and Chen, 2004), (Forczmański and Seweryn, 2010), (Fukunaga, 1990), (Messenger *et al*., 2023), (Wang, 2022), comparison, classification, detection of object features to determine whether given parts of an image contain a specific object. All of the above is aimed at obtaining quantitative and qualitative information about the studied objects relevant for further analysis. From the general group of image processing algorithms, those that can be used for processing and multi-camera and high-resolution video footage analysis have been selected. In accordance with the above considerations, the authors included within the scope of this study the possibility of extending the data acquisition model of vehicle traffic in urban zones, with new image data. The article proposes a model that has been prepared on the basis of real data, calibrated and verified against the analysed traffic streams. It's worth pointing out that the image data for the model were acquired simultaneously from several unmanned aerial vehicles, further expanding the area of analysis.

3.1. Research objectives

Due to the high degree of arbitrariness in the deployment of individual drones in a city, the authors propose a systemic approach, which consists of identifying study areas with four key factors for analysing urban transport nuisances. These are, respectively: the impact of dangerous gases emitted by road vehicles into the atmosphere, the places where the highest number of accidents involving cars and trucks accumulates, the density of traffic at different times of the day, and geospatial analysis of transportation corridors. With this approach, it is possible to apply the selection of research areas in any agglomeration.

An important element to consider, it turns out, is the need to synchronise the operating time of all flying units involved in the study of traffic streams. A timestamp read from the GNSS devices installed in the drones was used. This made it possible to eliminate possible errors in the readings of already processed information. Figure 1 shows a diagram of how the algorithm for analysing vehicle traffic streams using a

drone grid works. The acquired data must be collected on an external storage medium for further processing and analysis.

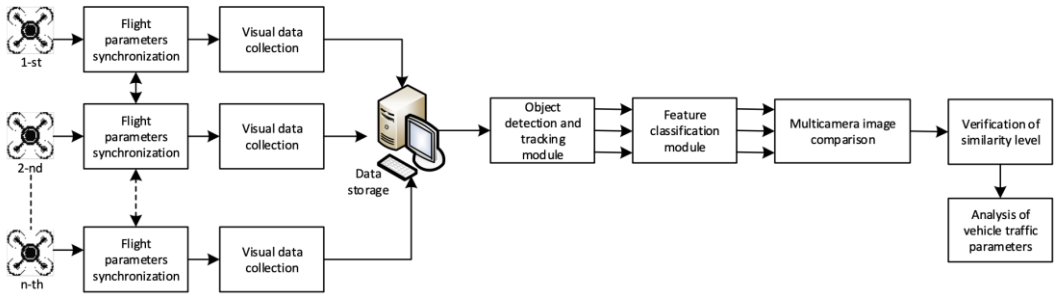


Figure 1. Diagram showing the use of a drone grid to study vehicle traffic streams, using algorithms for processing and analysing multi-camera images. Author's data

The goal set by the authors in this paper requires selection of appropriate and reliable methods for image processing and analysis. Due to the absence of ready-to-use, non-commercial solutions, the authors decided to implement some specific computer vision methods in a development environment, such as point-wise, contextual, convolutional, and morphological methods. In addition to preprocessing, using the above-mentioned methods, it was necessary to apply algorithms for detecting object features. An additional task that had to be fulfilled was to develop the fastest possible method of image processing and analysis. With such a goal set, the authors looked for methods that could be applied in real time. In the publication (Kujawski, 2022), experiments were conducted using a single industrial camera for object recognition. The computational performance and effectiveness of detecting and tracking moving vehicles using two independent neural networks, ResNet and YOLO 3, were tested, and the results of image processing speed and accuracy were compared with traditional computational methods. The results of the experiments showed a significant demand for computing power for both neural networks. In this article, traditional image processing and analysis methods were used in connection with the analysis of multi-camera images and the need to ensure real-time processing. For this reason, previously studied methods of vehicle classification using artificial neural networks were rejected.

3.2. Visual data acquisition

A number of trials and preliminary tests were conducted with a single, as well as several drones simultaneously. The flight parameters and parameters of the collected visual data were established during these tests. The best results were obtained for a drone flight altitude of 40 m, which gave a 40 x 60 m observation area. It is worth noting that drones can be used at any point in a city that is not in a no-fly zone (airports, factories, prisons, etc.), which gives great flexibility in the selection of measurement points. Another positive aspect of this approach is the ability to observe up to 10 lanes of vehicles moving in both directions simultaneously.

Figure 2 presents sample frames of images from three cameras mounted on unmanned aerial vehicles. The distances between the cameras were: 2.1 km between cameras 1 and 2, and 1.8 km between cameras 1 and 3. The purpose of such a deployment of the cameras was the need to cover the key points of the urban agglomeration in such a way as to allow analysis of vehicles entering and leaving the city centre. The method of filming and the vertical, aerial direction of video data collection was implemented so that the cameras did not interfere with the existing ITS infrastructure, and so that the recorded images did not include sensitive data about vehicles and drivers, such as license plates.

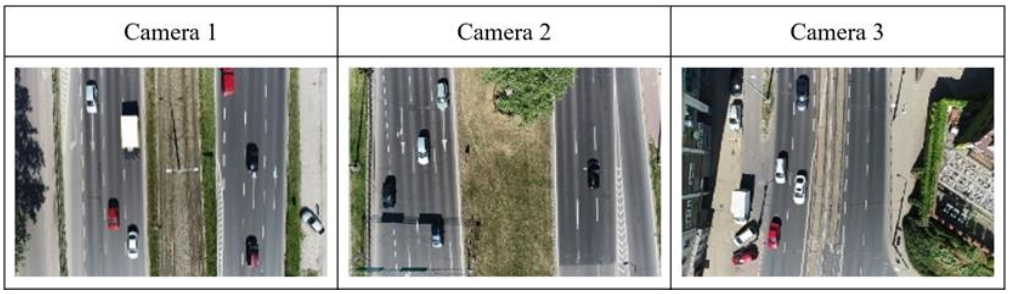


Figure 2. Sample images of traffic flow from three cameras mounted on unmanned aerial vehicles. Author's data

The final experiment used video footage with a total duration of about 2h. All images were time-synchronised with one other. Parameters such as altitude and flight duration of all three drones were identical. The recorded video footage was characterised by identical settings, such as white balance, resolution, aperture size and number of recorded image frames per second. A time of day just outside the morning traffic rush hour was chosen to record as many delivery vehicles as possible.

4. The experiment – Image processing and analysis

The purpose of this study is to use cameras mounted on UAVs for automatic analysis of image data on current traffic situations of urban logistics vehicles. Previous research on the feasibility of using computer vision methods provided an opportunity to select appropriate and reliable solutions from a group of methods for detecting and tracking object features. It became necessary to develop an algorithm for detecting vehicles in multiple images simultaneously. In connection with the different types of traffic situations observed, image processing which was resistant to changes in the scale of objects, as well as to changes in the angle of inclination of the observed objects became an important element. Each change in the observed key points represents a unique feature that is tracked throughout the image analysis process. The search for key points in each successive frame of the image sequence consists in comparing fragments of them with the template.

The authors developed and implemented an algorithm for multi-camera tracking of vehicles in urban traffic with a focus on recognising the routes taken by delivery trucks. A single object in motion was searched for until it was detected in another image from another camera. This approach provided the opportunity to analyse in detail the effectiveness of the selected methods and did not adversely affect the time required to process images from multiple cameras simultaneously. Algorithm 1 includes a procedure algorithm for detecting a vehicle and tracking it in multi-camera images. The algorithm used in this way provides an opportunity to use a drone grid to collect image data and its subsequent processing and analysis.

The goals of the main research experiment were to validate the proposed model for using a drone grid for analysing vehicle traffic streams and to verify the algorithm for detecting and tracking vehicles in multi-camera images. The use of three drones suspended in different parts of the city is the minimum number of devices to verify the validity of future use of any number of drones. The travel time of individual cars between measurement points ranged from 1.5 to 3.5 minutes.

Algorithm 1. Algorithm for multi-camera image data processing in vehicle traffic

```
Begin
   FOR each drone, continue until the observation is complete
        Store individual frames of the image in array variables
            D1 – Im1;
            D2 – Im2;
            Dn – Imn;
        WHILE the search object is defined:
          perform object feature extraction for Imn
          group identified object features
          save the object features to the Gfi array
        END WHILE
        IF a group of object features Gfi = vehicle Vej
          check the time of the object appearance tn
          track the object within the field of view
          map the object features for the remaining cameras, different from Imn
            FOR each Ve object detect characteristic features of the object for the remaining
                    cameras, different from Imn compare characteristic features on the current
                    and saved images (match)
                    IF the matching threshold is >= 60%
                        mark as a valid match track the object within the field of view check the time
                        of the tw object appearance compare the time Vt = tw - tn
                    END IF
                    ELSE resume searching for characteristic features
              END FOR
        END IF
        ELSE define a new search object
   END FOR
End
```

where:
D1 – Dn – UAV numbers;
Im1 – Imn – video image number;
Gfi – array of i-th object feature;
Vej – grouped features as j-th object;
tn – vehicle appearance time;
tw – vehicle field of view remaining time;
Vt – average velocity of moving vehicle

With this assumption, and possible changes in lighting conditions during this time, the effectiveness of the algorithm for recognising and detecting individual vehicles was tested on separate images collected

from independent video cameras. The entire research experiment was implemented in the Visual Studio programming environment using the OpenCV open computer vision library, in such a way that multiple camera images could be analysed simultaneously. The experiment proved very greedy for the computing power of the workstation, so several simplifications were made to make the experiment successful and run in real time. First, a single vehicle was searched for by multiple cameras simultaneously. Due to the project objectives of studying vehicle traffic in urban logistics, the focus was on freight transport vehicles. The variety of vehicles detected made it possible to assess the reliability of the automatic analysis and determine the confidence level at which the algorithm was able to automatically recognise the same object in multiple images.

5. Results

The lack of available non-commercial solutions for analysing images from multiple cameras simultaneously made it necessary to program a test environment. However, it could not be considered a finished application, as the high computational complexity did not allow testing all modules simultaneously. Nevertheless, it was possible to implement individual modules so that selected methods could be tested. It should be mentioned that in the future, in order to develop this concept, it will be necessary to integrate the individual modules into a coherent whole. Figure 4 shows selected screenshots of the working test environment. The screen of each example is divided into 4 parts. Three of them show the images from the individual cameras mounted on the drone, while the fourth window displays the results of the number of object features counted and the duration of analysis for a given vehicle, which corresponded to the length of vehicle detection in the camera's field of view.

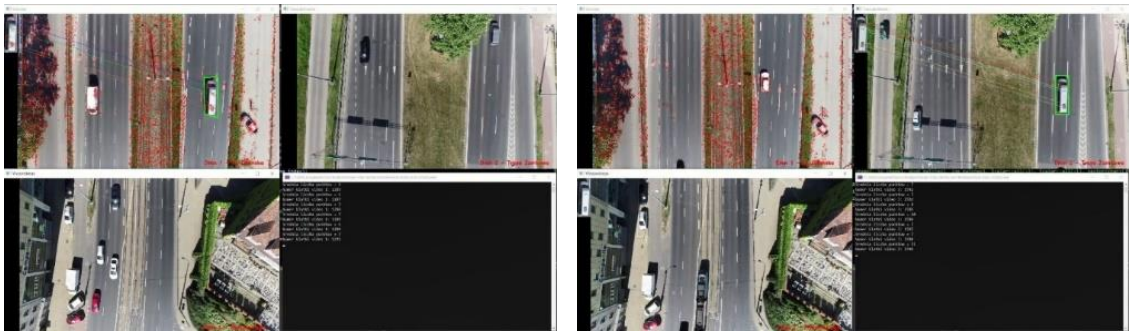


Figure 4. Examples of images from the test application for detecting moving vehicles in multi-camera images analysis. Author's data

Using three UAVs deployed simultaneously at selected points in the urban agglomeration, results were collected for 50 test vehicles to assess the suitability of the proposed methods for subsequent implementation. In order to reduce the computational data, the original 4K resolution images (3840 x 2160px) were reduced to 1080p (1920 x 1080). The maximum flight altitude was 40 meters, which was established experimentally for sufficient image recognition. The individual characteristics of detected moving vehicles were concentrated in two groups. The first group concerned the size of the set of moving pixels, in order to separate passenger vehicles from freight vehicles. The second group concerned the similarity of the characteristics of individual pixels and their surroundings. These were elements of shapes and colours (saturation, intensity) of individual parts of vehicles such as the bonnet, windscreen and roof. The counted features were searched for in other images collected by other drones in the multi-camera data collection system.

As a result of using the test environment software, the following parameters of the detected urban logistics vehicles were estimated: travel time, distance, estimated sectional speed of the vehicle, the number of detected characteristics, thanks to which it was possible to classify the vehicles and the place of appearance in a particular part of the city, which in turn allowed us to determine the routes of the tested vehicles. In addition, a percentage confidence level was determined based on a comparison of the number of detected characteristics, which made possible a visual assessment of the correctness of this analysis.

The Appendix A summarises the collected results of the experiment. The first two columns showing the frame numbers of detected vehicles were used to estimate the travel time of delivery vehicles between the measurement points. The rows without most of the data and the word 'none' in the last column indicate that the vehicle detected by the first camera did not appear in any of the surveyed locations, indicating that

it took a diversion and bypassed the city centre. In the column assessing the level of confidence in detecting vehicle features, one can see percentages ranging from 61.75% to 82.35% in each of the given cases, the algorithm correctly detected the desired vehicle. This leads to the conclusion that more than 60% of correctly detected features of a tracked object are sufficient for the algorithm to correctly classify the vehicle as recognised. Figure 5 illustrates the results of detecting the characteristics of correctly recognised vehicles in multi-camera images. The vertical lines reflect the differences in the searched and detected features, distinguishing the two analysed distances of 2.1 and 1.8 km.

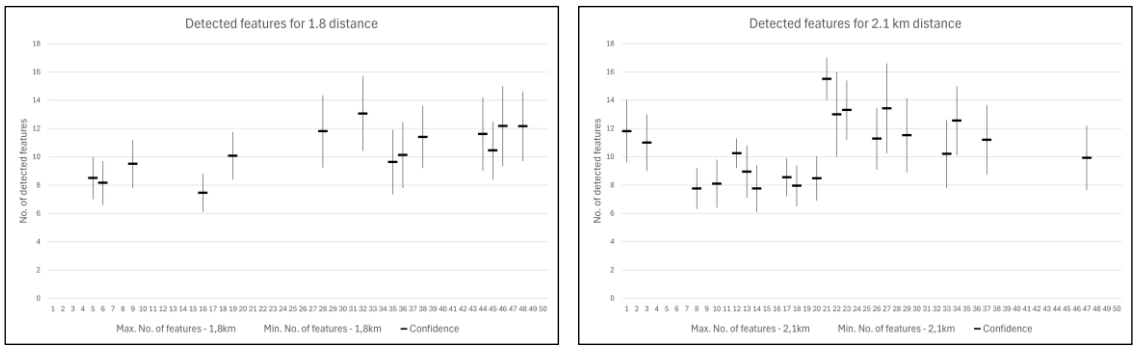


Figure 5. Numbers of detected and correctly classified object features for the distances studied 1.8 km (left) and 2.1 km (right). Author's data

As shown, differences in the number of detected characteristics do not significantly affect the confidence level for correct vehicle recognition. The method of detecting features of individual image pixels, as well as its surroundings, is based on the distances between the individual features and grouping them into sets belonging to a single object in motion.

Figure 6 on the left shows the confidence levels of detected object features. Except for two cases of classifying features at more than 80%, in the vast majority of cases the level of correctly read points remained above 60%. A correlation was noted that this level was sufficient for the algorithm to correctly assign a vehicle as correctly detected. Thanks to the conducted study, the correctness of the logical dependencies used in the algorithm was verified and satisfactory results of vehicle detection in multi-camera images were obtained.

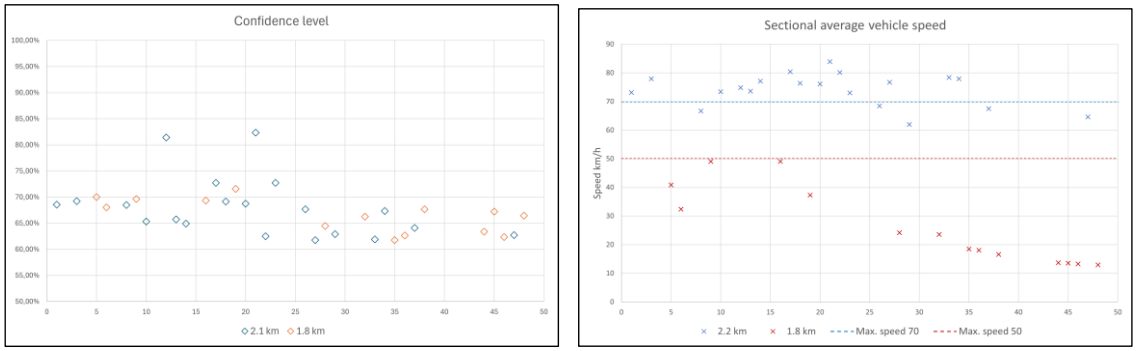


Figure 6. Confidence levels of individual detected vehicles (left). Estimated sectional speed of vehicles for distances of 2.1 km and 1.8 km (right). Author's data

An additional element of the conducted experiment was the possibility of studying the traffic parameters of city logistics vehicles, such as sectional speed measurement, routing of individual vehicles, or the number of vehicles entering and leaving the city centre.

Figure 6 on the right examines the estimated average sectional speed of moving vehicles. The dashed lines indicate the maximum permissible speed for the surveyed sections of urban roads, respectively, the red dotted line represents 50 km/h for a section of 1.8 km and the blue dotted line 70 km/h for a section of 2.1 km. It should be mentioned that the purpose of the study was not to detect irregularities in the movement of vehicles, but to test the correctness of the proposed algorithm for estimating the average movement

speeds of vehicles entering and leaving the city centre. It is possible to notice a clear decrease in the average speed of vehicles moving along the 1.8-kilometre section as the measurements proceeded, and thus a change in the road traffic volume as the afternoon rush hour approached. It provides a basis for determining the suitability of the proposed algorithm for the purpose of studying traffic flows in the city.

6. Conclusions

This paper proves the validity of the assumed hypothesis that the use of drone grids for video data acquisition and application of automatic image processing algorithms to generate useful information will complement the information resources of urban logistics systems. The data obtained in the study contributes to filling in the missing data from the field of urban logistics as to the volume and routes of freight transport.

The concept of drone grids and automatic image processing algorithms integration holds significant promise in enhancing urban logistics systems by providing valuable insights into vehicle traffic dynamics. Through rigorous testing and validation procedures, the proposed model showcases its efficiency in studying the flow of vehicles within urban environments, offering a pathway for decision-making. However, the successful deployment of this technology depends on addressing several logistical and technological challenges, e.g. the limited battery life of unmanned aerial vehicles (UAVs). Although manufacturers ensure flight times of up to 30 minutes, actual usage often offers a more conservative operational window of approximately 25 minutes per battery cycle. Moreover, the process of replacing batteries causes a brief pause in data collection. To address this issue, alternative solutions like inductive drone charging platforms or tethered drones offer promising potential. These options ensure an uninterrupted power supply, facilitating seamless and continuous data acquisition without the need for frequent battery replacement. Furthermore, careful consideration must be given to the selection and optimisation of video processing and analysis algorithms. Balancing factors such as performance, reliability, and processing time is crucial in ensuring effective operations.

Despite these challenges, the proposed methodology improves assessment of vehicle behaviour within city centres and makes broader applications in urban transportation planning possible. Through the integration of innovative detection and tracking techniques with strategic urban planning initiatives, this research study leads the way to efficiency enhancements in freight transport management, considering sustainable urban development. Consequently, the adoption of such approach would not only improve existing logistics processes, but also deliver valuable insights for future urban transport practices and efficient energy management, crucial for sustainable urban transport planning.

The research conducted was carried out as part of an international research project using a Polish-Norwegian financial grant. The main objective of the research project was to develop information tools to support urban logistics management and to study the environmental impact of urban freight transport. The impact of the use of modern information technologies on increasing the awareness of decision-makers involved in urban logistics management and planning about the current situation in cities was investigated.

The surveys conducted allowed to positively verify the main research hypothesis posed in the article "The application of drone grids for video data acquisition and utilisation of automatic image processing algorithms to generate useful information will enhance the information resources of urban logistics systems". We received positive responses from major stakeholders in expanding information resources. Municipal authorities are interested in using information automatically extracted from drones for operational and tactical decision-making needed for future strategic planning. An element to pay attention when using multiple drones simultaneously is the weather conditions, which have a significant impact on both the quality and reliability of vehicle detection, particularly fog which can decrease recognition accuracy. Rain, on the other hand, prevents recognition, as UAVs cannot operate during such weather. Our experiments were conducted only under clear weather conditions because this aspect was not the main focus of our study. Although it is an important direction for future study.

Further research into the use of drone grids and image processing and analysis methods will be concerned with increasing the automation of data acquisition and processing, taking into account dynamic changes in vehicle traffic streams. At present, the proposed method can serve as a complement to existing information resources for intelligent transport systems in cities or serve to verify the correctness and effectiveness of existing methods of acquiring and analysing vehicle traffic streams.

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Declaration of Generative AI and AI-assisted technologies in the writing process:

- During the preparation of this manuscript the author(s) did not used Generative AI and AI-assisted technologies and take(s) full responsibility for this declaration.

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