5G-Connected Drone for Public Road Safety - Research Challenges and Future Research Roadmap

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***Abstract* - 5G mobile communication infrastructure attracts increasing attention of stakeholders, going beyond only interconnection of people and increasingly serve to connect and manage 5G-enabled IoT devices. Among others, unmanned aerial vehicles (UAVs) or systems (UAS) already rely on 5G communication infrastructure and in the near future are envisioned to use it even more. 5G systems already support a wide-variety of different applications, such as remote healthcare, self-driving ground vehicles, virtual or augmented reality, drones, surveillance and many more. Among these is the high-resolution video surveillance using drones for different purposes. In road traffic analysis, one of the most important public safety applications, the low compressed or uncompressed video stream can greatly improve the analysis and traffic incident detection performance. On the other hand it is challenging to transmit high-resolution video stream in real time due to its data size. This paper provides an overview of the current research in the area of UAV command and control using 5G systems describing basic concepts and challenges. We review some of the latest research in regard to real-time high-resolution video transfer. A brief discussion of experiments on the 5G private campus network communication between a drone and a ground analytical system is presented.**

Keywords - UAV, remote control, performance evaluation, 5G, HD video stream, edge computing, proof-of-concept

I. Introduction

Advances in technologies behind *Unmanned Aerial Vehicles* (UAV), better known under the term ‘drones’, became omnipresent tool for different assignments, such are observation, emergency search and rescue, agriculture, public safety, object detection, communication and many other. Besides, the emergence of Fifth Generation cellular networks (5G) expands the scope of their applications and possibilities. It is expected that the advantages of 5G networks (enhanced broadband, reliable and low latency connections, mobile edge computing and networks slicing) will enable new innovative services and business opportunities.

This paper aims to examine some of the recent applications of 5G connected drones related to public road monitoring and traffic analysis. Also provided is a brief overview of some of the novel publicly available traffic datasets recorded by the drone cameras. Proposed is an experimental laboratory UAV platform for development of a real-time traffic detection and analysis system. Cellular connectivity was tested between the UAV and 5G base station (BS) in the laboratory environment, on a private, 5G campus network, providing experimental results on throughput and latency between the UAV and base station.

The rest of the paper is organized as follows: Section II briefly reviews some related work in regard to 5G connected drones and object detection. Publicly available drone datasets that are appropriate for machine learning tasks are discussed in Section III. Proposed platform architecture and experimental results from the laboratory environment tests are provided in Section IV.

II. Related work

In the field of drone development, a tremendous progress has been made in recent years. Since UACs are being continuously improved, they enter into the focus of interest of many research groups. There are many significant contributions related to challenges of limited drone computational resources and improvement to the wireless connectivity options and data throughput. When considering the application of 5G drone control networks, technological constraints and solutions both for communication and automatic video detection and analysis have to be taken into account.

3GPP Technical specification TS 22.125 version 17.3 from March 2021 [1] addresses several options for command and control communication (C2) between UAV controller and UAV, among others is the direct C2 communication established in a way both the UAV and UAV controller are registered to the 5G network. This type of connection is also the topic this article is focused on. The technical specification define requirements for remote UAV control using a high-definition (HD) video over the 5G network with minimal data rates of 300 Kb/s for C2, 25 Mbits/s for video transfer and end-to-end latency up to 20 ms. If a 4K video is considered, speed requirements are even more strict: 50 Mb/s for C2 and 120 Mb/s for video.

Taking the mentioned requirements into the consideration, the first part of this brief review provides overview of recent research in the area of cellular network application for controlling UAVs. Some of the research papers from recent years [2-4] already explored the results of cellular-connected drones using public 4G networks, especially regarding handovers and connection latency, data throughput. Public 4G networks usually provide an average throughput of a 10-50 Mbit/s both in downlink and uplink. But one of the main issues with cellular communication (thus also for cellular-connected UAVs) is that cellular modems experience line-of-sight (LoS) links to distant base stations. These cause unnecessary handovers, data connection interruption and consequently increase of connection latency.

One of the recently published research papers in 2020. is [5] where authors present experimental results on the cellular communication between an UAV and a commercial 5G network. Analyzed were link quality, throughput, and handovers. Carried were three types of tests and measurements: during the liftoff phase and during flights at 30 and 100 m. As experiments were conducted on the public mobile network, there were handovers between 4G and 5G. In regard to transfer speeds, the research concludes that the UAVs in real fight conditions can receive several hundred Mbit/s over 5G, which is satisfactorily for most of the applications.

Due to different issues related to network connectivity, [6] proposes a closed-loop control solution for Open RANs to support drone-based video streaming applications on commercial cellular networks, providing 19% network capacity gain with better adaptability to network conditions and changes. *Horizon 2020* project "*5G!Drones*" aims to trial several UAV use-cases covering different 5G network services (eMBB, URLLC and mMTC) and providing reference design demonstrating how 5G can support U-space services [7]. Among these use-cases is the UAV situation awareness and public safety. Work [8] presented 5G-enabled UAV prototype with a virtualized flight-controller onboard computer at the edge of the 5G cellular network. By the offloading of resource demanding tasks from the drone optimization of UAV energy consumption is achieved.

For analytical processing of video gathered by UAV the most common computer vision methods used are CNN, R-CNN and Optical flow [9-16]. These processing methods are mainly used for detection and tracking of different objects in video sequence offering different levels of performance. Optical flow is the movement of objects between successive video frames, which is a consequence of the relative movement between the object and the camera. In the domain of image processing, the intensity of the frame of the video sequence (I) can be expressed as a function of space (x, y) and time (t). Then the optical flow problem can be mathematically expressed as the displacement of a point spatially determined with coordinates (x, y) to a new position in the image within the time period dt. Optical flow is method which doesn't use any marked data-sets and because of that it can be easier to implement than CNN and R-CNN based methods which need marked data-sets to detect and track the object. Despite not using trained neural networks for detection and tracking of the objects in video stream optical flow methods can show good performance for tracking an object from the UAV as it is seen in papers [15] [17-18]. Since optical flow is mathematically based on tracking the moving pixels in the picture there is always a challenge in implementing this method on UAV based camera systems because of relative movement between UAV and detected object. However, there are ways of compensating for the movement which has already been done successfully in multiple papers [18] [19].

There are also multiple open-source based tools for detection, classification and tracking of the objects in video. Most of the open source tools are CNN based, for example *Faster R-CNN* [20], *Detectron* [21], *SlimYOLOv3* [22] and *OpenDataCam* [23], but there are also ones which implement detection and analysis using optical flow method [19] [24]. These tools are not optimized for videos which are taken from the UAVs so using this or any other open source tools is a good starting point for a future research but it also requires additional fine tuning for videos which are taken by UAVs.

III. DRONE DATASETS FOR IMPROVED VISION TRAFFIC ANALYSIS

Application of an unmanned aerial vehicle removes typical limitations of common traffic data collection tools due to the aerial view. On the other hand, vision analysis and object detection is a challenging task in general, especially when considering video or images received from camera placed on an UAV. Issues related to camera shooting angle and height changing during the flight, weather conditions and drone stability are some of the challenges that must be considered. As drones that are used for road traffic monitoring usually fly on relatively high altitudes (80-120 m), drone camera view covers larger area, but the target objects are very small on the shot video frames compared to their actual size (sometimes only a few dozen pixels in size). Complex object motions, variation in picture or video quality, reflection from objects are also some of the problems. Due to all these issues commonly used techniques and algorithms for vehicle detection, object tracking and analysis of traffic flow parameters (speed, density etc.) are not applicable. Video surveillance employing drones is the focus of many research groups, to which contribute advances of automated object detection and classification using artificial intelligence (AI) / machine learning (ML) techniques in recent years. In order to improve performance of these AI/ML based methods, it is necessary to use annotated videos and images during the training of the algorithm [25].

This part of a paper covers some of the available traffic datasets recorded by the drone cameras. There are a number of datasets containing different records of naturalistic road user trajectories (cars, vans, buses, pedestrians, bicycles etc.) in different environments and from different countries. It is important to note not all of them contain images and/or videos, but some only annotated data.

Institute for Automotive Engineering (ika) of RWTH Aachen University and fka GmbH, Germany, have prepared several drone datasets containing road user trajectories recorded at roadways, *highD* [26], four intersections, *inD* [27] and three different roundabouts, *rounD* [28] in Germany, including all common road entities. Datasets do not contain the original aerial images or videos. The *highD* dataset [26] contains road user trajectories recorded at six different locations, including 110 500 vehicles, 44 500 driven kilometers and 147 driver hours. All three datasets contains annotations for each road user and its type, including vehicles (car, lorries, trailers, vans, buses), pedestrians, bicyclists and motorcycles. The authors state the positional error is typically under 10 cm. Provided are scripts for Python used for parsing the provided files and visualization of annotated trajectories. These datasets can be applied not only to traffic analysis, but also to driver and pedestrian modeling, different traffic predictions and safety validation of Automated Driving Systems. All three datasets (*inD*, *highD* and *rounD*) are free for non-commercial use only, but a commercial license is also possible to obtain.

The *VisDrone2021* dataset [29] is prepared and regularly updated by the Lab of Machine Learning and Data Mining, Tianjin University, China. This dataset is consisted of several parts used for object detection in images, multi-object tracking and crowd counting. It was and is still used for workshops related to computer vision research. It contains 400 video clips and 10 209 static images. Various drone-mounted cameras were used under various weather and lighting conditions, in 14 cities in China, covering urban and rural environment, different entities (vehicles, bicycles, pedestrians, etc.). According to authors, dataset was manually annotated including important attributes including scene visibility, object class and occlusion. Dataset size is around 10 GB and is free to access.

The *Multi-view Traffic Intersection Dataset* (MTID) [30] is a traffic monitoring dataset containing specific, simultaneous recording of the same intersection with complex traffic scenes from multiple points of view. Two synchronized viewpoints come from camera mounted on existing infrastructure or gantries, and a camera mounted on a drone. Traffic in all views has been annotated. This dataset provides the ability to analyze the distinctions between different viewpoints. The dataset is freely available online.

The *Stanford Drone Dataset* [31] is created by the Computational Vision and Geometry Lab (CVGL) at Stanford University. It provides collection of images and videos of various types of entities (pedestrians, bicyclists, skateboarders, cars, buses etc.) that move in the outdoor environment. The dataset is published under the *Creative Commons Attribution-NonCommercial-ShareAlike 3.0 License* with additional option for commercial usage. It is around 69 GB in size available for download.

The *CyCAR Dataset* [32] is provided by the Intelligent Digital Systems Lab at Imperial College London and the KIOS Research and Innovation Center of Excellence at the University of Cyprus. It is based on the UAV recordings above the city of Nicosia in Cyprus. It contains 27 min of high-resolution video with cameras positioned vertical to the ground, with a minimum and maximum levels between 20 and 500 m above the ground. The annotated frames span from heavily congested to clear traffic situations. Its current size is around 13 GB available for download under an *Open Data Commons (ODC) Attribution License*.

The *DroneTrafficZA2020 Dataset* [33] is provided by the University of Pretoria, South Africa. It contains 4K video about 18 minutes in length together with vehicle detection, classification and counting data. Automatic object detection and counting of object was done using *OpenDataCam* [23]. The dataset was created to test traffic classification and speed quantization methods using artificial intelligence implemented of a low-cost computing platform for long-term real-time traffic monitoring and analysis applications. It is around 3 GB in size available for download under the *Creative Commons Attribution 4.0 International license*.

The Ohio State University, Columbus, United States, provided two datasets with top-view trajectory data of pedestrians in crowd under vehicle influence: *Vehicle-Crowd Intraction (VCI)* - DUT and CITR Datasets [34]. There are around 340 pedestrian trajectories in CITR dataset and 1793 pedestrian trajectories in DUT dataset. The Github project web site also provides a link to the raw video recordings of both datasets. The files are around 730 MB in size available for free access.

IV. Proposed Platform Architecture and Experimental Setup

The purpose of preliminary study was to analyze campus network 5G data connection applicable to traffic

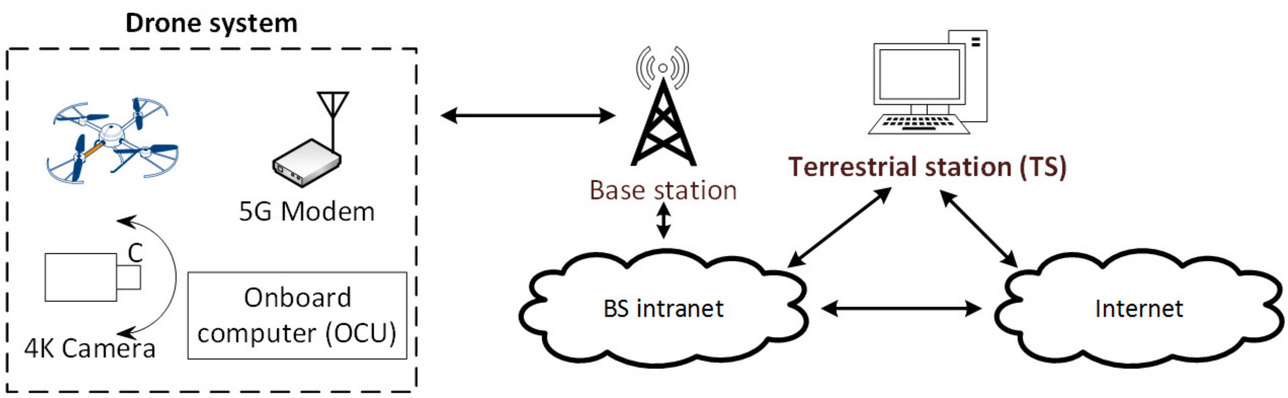

Figure 1. Proposed test system architecture

TABLE 1. NETWORK PERFORMANCE RESULTS

Experiment	Link	Throughput (Mb/s)			Latency (ms)
		maximum	average	stdev	
BS intranet	DL	871	746	194	~ 1 ms
	UL	159	147	21	~ 1 ms
Internet	DL	725	587	213	~ 9 ms
	UL	133	111	16	~ 10 ms

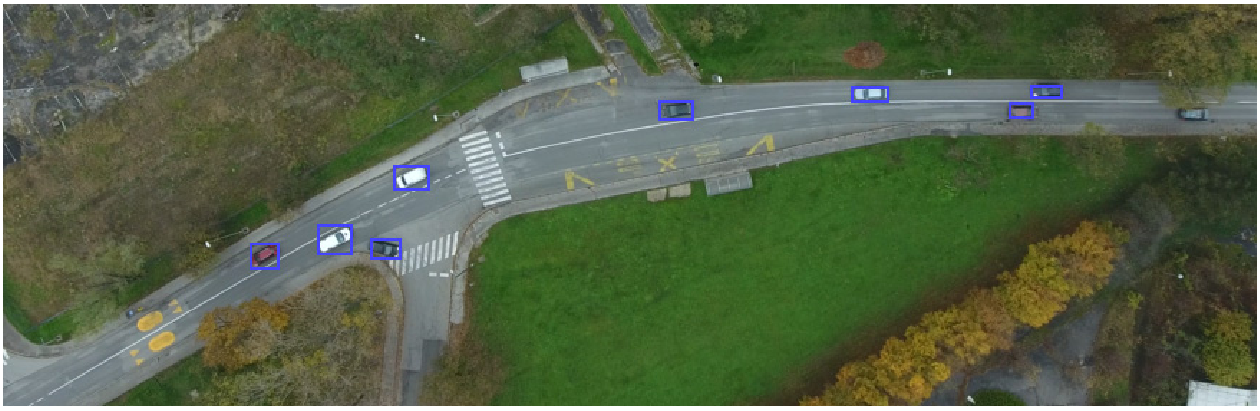

Figure 2. Screenshot of a traffic detection operation (blue bounding boxes indicate final results)

surveillance UAV. Experimental platform (Fig. 1) is designed to be flexible for future research and consists of two main components: a) drone system, b) terrestrial station controller. Drone system consists of the following: an open-source based developer hexacopter UAV platform with a dedicated onboard computer unit (OCU) running Linux Debian, equipped with 5G sub.6 M.2 format modem module, 4K camera and a backup drone radio transceiver. Terrestrial station (TS) is a computer equipped with a multicore CPU (i7), GPU (RTX 2080S), 64 GB RAM, running proprietary commercial OS with wired Ethernet connection to the local cellular base station (BS) intranet or public Internet and a backup drone radio controller. The 5G base station used 3.6 GHz band. The drone radio controller was provided only for basic UAV telemetry debugging and was not used during the tests. The idea to have a processing system on the ground instead on the UAV improves its energy efficiency, as the OCU serves only to control the UAV and to encode the video using the H.264 video compression.

The preliminary experiments were performed in one of the laboratories at the Faculty of Electrical Engineering and Computing in Zagreb, where a small private 5G campus network is operated. As the drone could not be operated in a real environment over the private 5G network due to its modest coverage, a half hour recording of the road traffic was previously prepared with the UAV platform. It is important to emphasize that no UAV was flown using a 5G network, but proposed system components were only tested in a controlled lab environment and only the prerecorded video was streamed over the 5G data link.

For the purpose of the 5G network connection properties tests, a previously made road traffic recording was only played through the UAV platform components, thus simulating camera recording and streaming through UAV OCU using onboard 5G modem. There were several measurements of static data link properties conducted: simultaneous upload and download tests between OCU connected to 5G campus network and TS that was in the first group of tests connected to local BS intranet and afterwards to the public Internet. Connection to a local BS intranet was used to perform network performance tests without any external influences to the data link, except BS and radio. Tools used for connection performance measurements were iPerf3 (installed both on OCU and TS) and a custom-built UAV control client-server application where the server part resides on the OCU, and client part on the TS.

Results provided in Table 1 should be considered taking into account that the tests were conducted in highly-controlled laboratory environment. Thus measurements were not affected by actual influences that can certainly occur in actual, real-world UAV operating conditions. Direction DL is referred to data transfer from TS towards UAV/OCU, while direction UL is referred to data transfer from UAV/OCU towards TS. Download throughput results were somewhat expected for these basic tests, but Internet connection had a significantly higher latency than expected. This discrepancy is related to the internal configuration of 5G campus network at the time tests were performed and requires further research. On the other hand, campus 5G network implementation did not significantly improved upload (UL) throughput, but was sufficient to provide video stream transfer to ground TS.

The second part of the experiment was to test TS hardware platform for analysis of two prerecorded traffic videos taken from 80 m and 120 m, in total length of about 10 minutes each. For this purpose a SlimYOLOv3 [22] open-source detector was evaluated, as shown on Fig. 2. Preliminary tests confirmed the previously described hardware platform of TS is sufficient. The detection of larger object such as buses and cars was successful with detection rate of 91 % in both recordings. On the other hand, detection rate of smaller objects, like pedestrians and bicycles was only 18 %, mainly due to lack of well-annotated training data. It is therefore necessary to direct future research towards improving the train data quality, especially for smaller targets.

V. Conclusion

Paper introduced a brief overview of a current research in the field of UAV control over the public 5G communication networks describing basic concepts and challenges. Presented was an early prototype of a 5G-enabled UAV system, demonstrating application of low latency 5G network drone control, utilizing terrestrial computer for soft-real-time road traffic detection and analysis. Future research will be directed towards exploring the C2 communication where the UAV is provided with a pre-scheduled flight plan and still maintains a C2 communication link with the terrestrial station in order to monitor the flight status of the UAV and update flight plans in real-world environment. Also a comparison of public 4G and 5G network connection performances will be made.

Open source frameworks and computer vision methods for detection, classification and tracking of the vehicles from UAV based videos have been researched and brief overview of them is given in this paper. Future research will be focused to deeper analysis and comparison of open source tools used for different objects detection in aerial images of public roads and development of a specialized computer vision analysis solution which can be used for public road safety purpose.

References

[1] ETSI 3GPP TS 22.125 version 17.3.0; "Unmanned Aerial System (UAS) support in 3GPP", https://www.3gpp.org/ftp/Specs/archive/22_series/22.125/

[2] G. E. Athanasiadou; M. C. Batistatos; D. A. Zarbouti; G. V.Tsoulos; "LTE ground-to-air field measurements in the context of flying relays", IEEE Wireless Communications, 26(1):12-17, 2019.

[3] S. Hayat; C. Bettstetter; A. Fakhreddine; R. Muzaffar; D. Emini; "An experimental evaluation of LTE-A throughput for drones", Proc. ACM Workshop on Micro Aerial Vehicle Networks, Systems, and Applications (DroNet), 2019.

[4] H. C. Nguyen; R. Amorim; J. Wigard; I. Z. Kovaacs; T. B. Srensen; P. E. Mogensen; "How to ensure reliable connectivity for aerial vehicles over cellular networks. IEEE Access, 6:12304-12317, 2018.

[5] R. Muzaffar; C. Raffelsberger; A. Fakhreddine; J. L. Luque; D. Emini, C. Bettstetter; "First experiments with a 5G-Connected drone" 2020 Proceedings of the 6th ACM Workshop on Micro Aerial Vehicle Networks, Systems, and Applications (DroNet '20), Association for Computing Machinery, New York, NY, USA, Article 7, 1–5. DOI:https://doi.org/10.1145/3396864.3400304

[6] L. Bertizzolo; T. X. Tran; J. Buczek; B. Balasubramanian; R. Jana; Y. Zhou; T. Melodia; "Streaming from the Air: Enabling High Data-rate 5G Cellular Links for Drone Streaming Applications", Computing Research Repository CoRR abs/2101.08681 (2021), issn: 2331-8422

[7] S. Si-Mohammed et al.; "Supporting Unmanned Aerial Vehicle Services in 5G Networks: New High-Level Architecture Integrating 5G With U-Space," in IEEE Vehicular Technology Magazine, vol. 16, no. 1, pp. 57-65, March 2021, doi: 10.1109/MVT.2020.3036374

[8] Koumaras, H.; Makropoulos, G.; Batistatos, M.; Kolometsos, S.; Gogos, A.; Xilouris, G.; Sarlas, A.; Kourtis, M.-A; "5G-Enabled UAVs with Command and Control Software Component at the Edge for Supporting Energy Efficient Opportunistic Networks", Energies 2021, 14, 1480. https://doi.org/10.3390/en14051480

[9] Bertizzolo, L.; Tuyen X. Tran; John Buczek; Bharath Balasubramanian; R. Jana; Yin-qing Zhou; T. Melodia; "Streaming from the Air: Enabling High Data-rate 5G Cellular Links for Drone Streaming Applications." ArXiv abs/2101.08681 (2021): n. pag.

[10] X. Yongzheng; Y. Guizhen; W. Yunpeng; W. Xinkai; M. Yalong; "Car Detection from Low-Altitude UAV Imagery with the Faster R-CNN", Journal of Advanced Transportation, vol. 2017, Article ID 2823617, 10 pages, 2017. https://doi.org/10.1155/2017/2823617

[11] R. Ke; Z. Li; S. Kim; J. Ash; Z. Cui;Y. Wang; "Real-Time Bidirectional Traffic Flow Parameter Estimation From Aerial Videos", IEEE Transactions on Intelligent Transportation Systems, vol. 18, no. 4, pp. 890-901, April 2017, doi: 10.1109/TITS.2016.2595526

[12] M. Brahimi; S. Karatzas; J. Theuriot; Z. Christoforou; "Drones for Traffic Flow Analysis of Urban Roundabouts", International Journal of Traffic and Transportation Engineering, p-ISSN: 2325-0062 e-ISSN: 2325-0070, 2020; 9(3): 62-71, doi:10.5923/j.ijtte.20200903.02

[13] S. Javadi; M. Dahl; M. I. Pettersson; "Vehicle Detection in Aerial Images Based on 3D Depth Maps and Deep Neural Networks," in IEEE Access, vol. 9, pp. 8381-8391, 2021, doi: 10.1109/ACCESS.2021.3049741.

[14] X. Li; X. Li; Z. Li; X. Xiong; M. O. Khyam; C. Sun; "Robust Vehicle Detection in High-Resolution Aerial Images with Imbalanced Data," in IEEE Transactions on Artificial Intelligence, doi: 10.1109/TAI.2021.3081057

[15] L. Wang; F. Chen; H. Yin; "Detecting and tracking vehicles in traffic by unmanned aerial vehicles," Autom. Construction, vol. 72, pp. 294–308, Dec. 2016, doi: 10.1016/j.autcon.2016.05.008.

[16] E. Kim; H. Park; S. Ham; S. Kho; D. Kim; "Extracting Vehicle Trajectories Using Unmanned Aerial Vehicles in Congested Traffic Conditions", Journal of Advanced Transportation, vol. 2019, Article ID 9060797, 16 pages, 2019. https://doi.org/10.1155/2019/9060797

[17] G. Mo; S. Zhang; "Vehicles detection in traffic flow," in Proc. 6th Int. Conf. Natural Comput., Yantai, China, Aug. 2010, pp. 751–754, doi: 10.1109/ICNC.2010.5583178

[18]] Dahl, M.; Javadi, S.; "Analytical Modeling for a Video-Based Vehicle Speed Measurement Framework", Sensors 2020, 20, 160. https://doi.org/10.3390/s20010160

[19] De Bruin, A.; Booyse, M.J.; "Drone-based traffic flow estimation and tracking using computer vision", South African Transport Conference, Pretoria, 2015, https://doi.org/10.13140/RG.2.1.1024.6888

[20] S. Ren; K. He; R. Girshick; J. Sun, "Faster R-CNN: towards real-time object detection with region proposal networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017., https://github.com/ShaoqingRen/faster_rcnn

[21] R. Girshick, I. Radosavovic, G. Gkioxari, P. Doll, K. He, "Detectron", https://github.com/facebookresearch/detectron, 2018

[22] P. Zhang, Y. Zhong and X. Li; "SlimYOLOv3: Narrower, Faster and Better for Real-Time UAV Applications," 2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW), 2019, pp. 37-45, doi: 10.1109/ICCVW.2019.00011

[23] B. Groß; M. Kreutzer; R. Reimann; F. Porada; "OpenDataCam - An open source tool to quantify the world", https://github.com/opendatacam, 2021.

[24] Bradski, G.; "The OpenCV Library", Dr. Dobb's Journal of Software Tools, 2000., https://github.com/opencv/opencv

[25] S. Sambolek and M. Ivašić-Kos, "Detecting objects in drone imagery: a brief overview of recent progress," *2020 43rd International Convention on Information, Communication and Electronic Technology (MIPRO)*, 2020, pp. 1052-1057, doi: 10.23919/MIPRO48935.2020.9245321.

[26] R. Krajewski; J. Bock; L. Kloeker;L. Eckstein; "The highD Dataset: A Drone Dataset of Naturalistic Vehicle Trajectories on German Highways for Validation of Highly Automated Driving Systems," 2018 21st International Conference on Intelligent Transportation Systems (ITSC), 2018, pp. 2118-2125, doi: 10.1109/ITSC.2018.8569552, https://www.highd-dataset.com/

[27] Bock, J.; Krajewski, R.; Moers, T.; Runde, S.; Vater, L.; Eckstein, L.; "The inD Dataset: A Drone Dataset of Naturalistic Road User Trajectories at German Intersections", arXiv preprint arXiv:1911.07602, 2019, https://www.ind-dataset.com

[28] R. Krajewski; T. Moers; J. Bock; L. Vater; L. Eckstein; "The rounD Dataset: A Drone Dataset of Road User Trajectories at Roundabouts in Germany," 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), 2020, pp. 1-6, doi: 10.1109/ITSC45102.2020.9294728, https://www.round-dataset.com/

[29] P. Zhu; L. Wen; D. Du; X. Bian; Q. Hu; H. Ling; "Vision Meets Drones: Past, Present and Future", arXiv preprint arXiv:2001.06303 (2020), http://aiskyeye.com/

[30] M. B. Jensen; A. Møgelmose; T. B. Moeslund; "Presenting the Multi-view Traffic Intersection Dataset (MTID): A Detailed Traffic-Surveillance Dataset," 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), 2020, pp. 1-6, doi: 10.1109/ITSC45102.2020.9294694, https://vap.aau.dk/mtid/

[31] A. Robicquet; A. Sadeghian; A. Alahi; S. Savarese; "Learning Social Etiquette: Human Trajectory Prediction In Crowded Scenes" - Stanford Drone Dataset, European Conference on Computer Vision (ECCV), 2016., https://cvgl.stanford.edu/projects/uav_data/

[32] A. Kouris; C. Kyrkou; C.S. Bouganis; "Informed Region Selection for Efficient UAV-based Object Detectors: Altitude-aware Vehicle Detection with CyCAR Dataset", 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019, https://www.imperial.ac.uk/intelligent-digital-systems/cycar/

[33] Broekman, A.; Gräbe, P. J.; Steyn, W.; "DroneTrafficZA2020: A sample dataset of N4 freeway traffic adjacent to Engineering 4.0 in South Africa", 2020, Mendeley Data, V1, doi: 10.17632/wdfkxsnpzc.1, https://data.mendeley.com/datasets/wdfkxsnpzc/1

[34] D. Yang; L. Li; K. Redmill; Ü. Özgüner; "Top-view Trajectories: A Pedestrian Dataset of Vehicle-Crowd Interaction from Controlled Experiments and Crowded Campus," 2019 IEEE Intelligent Vehicles Symposium (IV), 2019, pp. 899-904, doi: 10.1109/IVS.2019.8814092, https://github.com/dongfang-steven-yang