remote sensing

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AERO: AI-Enabled Remote Sensing Observation with Onboard Edge Computing in UAVs

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Abstract: Unmanned aerial vehicles (UAVs) equipped with computer vision capabilities have been widely utilized in several remote sensing applications, such as precision agriculture, environmental monitoring, and surveillance. However, the commercial usage of these UAVs in such applications is mostly performed manually, with humans being responsible for data observation or offline processing after data collection due to the lack of on board AI on edge. Other technical methods rely on the cloud computation offloading of AI applications, where inference is conducted on video streams, which can be unscalable and infeasible due to remote cloud servers' limited connectivity and high latency. To overcome these issues, this paper presents a new approach to using edge computing in drones to enable the processing of extensive AI tasks onboard UAVs for remote sensing. We propose a cloud–edge hybrid system architecture where the edge is responsible for processing AI tasks and the cloud is responsible for data storage, manipulation, and visualization. We designed AERO, a UAV brain system with onboard AI capability using GPU-enabled edge devices. AERO is a novel multi-stage deep learning module that combines object detection (YOLOv4 and YOLOv7) and tracking (DeepSort) with TensorRT accelerators to capture objects of interest with high accuracy and transmit data to the cloud in real time without redundancy. AERO processes the detected objects over multiple consecutive frames to maximize detection accuracy. The experiments show a reduced false positive rate (0.7%), a low percentage of tracking identity switches (1.6%), and an average inference speed of 15.5 FPS on a Jetson Xavier AGX edge device.

Keywords: unmanned aerial vehicles; object detection; object tracking; remote sensing; object localization; edge computing; inspection; YOLOv4; YOLOv7; DeepSORT

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Citation: Koubaa, A.; Ammar, A.; Abdelkader, M.; Alhabashi, Y.; Ghouti, L. AERO: AI-Enabled Remote Sensing Observation with Onboard Edge Computing in UAVs. *Remote Sens.* **2023**, *15*, 1873. https://doi.org/10.3390/rs15071873

Academic Editors: Wenjiang Huang, Giovanni Laneve, Yingying Dong and Chenghai Yang

Received: 3 March 2023
Revised: 27 March 2023
Accepted: 29 March 2023
Published: 31 March 2023

1. Introduction

The use of unmanned aerial vehicles (UAVs), also known as drones, in remote sensing has been increasingly beneficial as they help to speed up the data collection of assets of interest using aerial images. Drones make the data collection process cost-effective and flexible as drones can fly at low or high altitudes. It also helps missions to be more efficient as large regions can be precisely covered in short times thanks to the use of high-resolution cameras. Data collection also becomes safe as drones replace humans entering dangerous or difficult-to-access environments. These benefits are driving the remote sensing business to increasingly rely on drones. As a matter of fact, the market of commercial use of UAVs, including remote sensing applications, was valued at USD 5.85 billion in 2020 and is expected to have a compound annual growth rate of 14.2% [1].

1.1. Motivating Scenarios

AI-powered drones with onboard intelligence are becoming a game changer for many applications, including search and rescue, rapid infrastructure inspection, and remote sensing, to name a few. Integrating AI solutions directly on the drone's edge (compute) devices can dramatically reduce the decision-making time and operational costs. In this paper, we will discuss several scenarios in different use cases' contexts, showing the limitation of existing solutions of UAVs for vision-based applications and discussing the advantages of real-time onboard AI.

1.1.1. Remote Sensing

Tree counting is one of the applications in remote sensing, where a drone surveys farm regions to count the number of trees. In [2], the authors proposed an offline counting and geo-localization of palm trees based on aerial images using deep learning. However, the processing was performed offline after collecting palm tree images from a UAV. The process of data collection and its offline processing takes a long time and needs to be performed in real time. Leveraging GPU-based edge devices on board the UAV enables the full automation of palm tree counting in real time. Furthermore, it helps to send each palm tree information (e.g., image and coordinates) to the cloud and store it in databases in real time. Naturally, the same concept can be applied to other remote sensing applications, such as gas leakage localization and mapping [3], flash flood real-time monitoring [4,5], and urban environment segmentation [6,7].

1.1.2. Search and Rescue

Consider a search-and-rescue mission where a drone is required to explore an extended region to search for a missing person in the desert or a forest, for example. It has been reported that more than 100 people get lost and die in the desert annually in Saudi Arabia alone [8]. The current practice for search-and-rescue using UAVs is to manually explore a region with human observers to find the target missing people. Using AI on board will help to automate the process as the UAV can execute specialized person detection models on board and automatically report their location in real time. It is also possible to use a swarm of drones to perform search-and-rescue missions in parallel, speeding up the search process and increasing the probability of finding and saving people [9].

1.1.3. Inspection and Surveillance

Surveillance and inspection using UAVs is one of the fastest businesses in the drone industry [10]. Drones are typically used to detect objects of interest in surveillance missions, such as vehicles [11], pedestrians [12], and buildings [13]. Traditional approaches either inspect real-time video streams by human observers or record scenes' videos and process them offline either manually or using AI techniques to extract target objects. The use of onboard AI processing in the UAVs will help to automate the inspection process and identify target objects in real time with a high accuracy, as will be demonstrated in this paper.

The automation of these applications on board UAVs is possible thanks to the evolution of edge devices and their support of advanced graphics processing units (GPUs), making it possible to process complex deep learning models in real time.

Before the evolution of edge computing, computation offloading has evolved as the prominent approach to processing heavy computation in the cloud instead of processing them on robots or drones. This concept has been known as cloud robotics. While computation offloading offers several advantages by leveraging the capabilities of the cloud resources to speed up the processing of deep learning models and computation-intensive applications, it suffers from high communication overhead. It also needs a large bandwidth and high-quality communication, which cannot always be afforded. In [14], the authors proposed a system architecture for computation offloading in Internet-connected drones and compared the performance of cloud computation offloading versus edge computing for deep learning applications. The study investigated the tradeoff between the communication cost and computation and found that computation offloading provides higher throughput despite larger communication delays.

1.2. Main Contributions

In this paper, we aimed to tackle the persisting challenge of deploying onboard artificial intelligence on the edge in commercial unmanned aerial vehicles (UAVs) that are primarily utilized for remote sensing applications. This predicament often necessitates laborious manual data observation or time-consuming offline processing, as cloud-based approaches are often impractical. There are a few recent works that tested onboard AI on edge in UAVs for detection and tracking, such as [15–17]. Nevertheless, they did not investigate the hybrid system architecture that we implemented in this work, and did not discuss the role of the cloud in their solution. To bridge this gap, we propose using edge computation on board drones to enable advanced observation and surveillance applications, involving object detection, multi-object-tracking, and real-time reporting of detected target objects to the cloud. In brief, the contributions of the paper can be summarized as follows:

- We propose a new approach to using edge computing in drones to enable the processing of extensive AI tasks on board UAVs for remote sensing. To overcome the limited connectivity and high latency of remote cloud servers, we propose a cloud–edge hybrid system architecture. In this architecture, the edge is responsible for processing AI tasks, and the cloud is responsible for data storage, manipulation, and visualization. Our proposed architecture can provide a more scalable and efficient solution for remote sensing applications.
- To implement our proposed architecture, we designed and developed AERO, a UAV brain system with onboard AI capability using GPU-enabled edge devices. AERO allows us to capture objects of interest with high accuracy and transmit data to the cloud in real time without redundancy. AERO processes the detected objects over multiple consecutive frames to maximize detection accuracy. AERO can be a significant advancement in the field of remote sensing as it enables UAVs to perform onboard AI tasks with high accuracy and real-time data transmission, providing a more efficient and cost-effective solution for remote sensing applications.

The remaining sections of the paper are organized as follows. Section 1.3 provides a review of the relevant literature and situates the contribution of the paper in comparison to previous work. Section 2 presents the architecture of the AERO system and describes the AERO AI Module. In Section 3, we detail the experimental study conducted to evaluate the AERO system's performance, and we discuss their results in Section 4. Finally, Section 5 concludes the paper and suggests potential future research directions for further improvements.

1.3. Related Works

The introduction of UAVs in remote sensing has paved the way for several promising applications that span a wide range of domains [18]. Impressive progress has been achieved in academic and industrial arenas. Diversity in available solutions is mainly attributed to the underlying technologies and modalities used in the data sense/acquisition processes [19]. The latter processes are domain-specific in nature [20,21]. Other techniques, including data preprocessing, feature extraction, and classification, are specifically designed for the application, whether civilian or military. UAV applications in remote sensing have been reviewed in [21,22].

1.3.1. Edge Computing and UAVs

Several recent works addressed the edge computing paradigm, which involves moving computational processing and storage closer to the end-users, devices, or sensors rather than relying solely on cloud-based solutions. Specifically, these works focused on leveraging UAVs to offload computation tasks to edge computing servers, which enables low-latency computations of specific tasks without noticeable delay.

In [23], Messous et al. proposed an evaluation mechanism of the integration of the computation offloading to edge computing servers for the efficient deployment of UAVs.

Based on the proposed evaluation, UAV-based models are able to decide whether to perform local processing, offload to an edge server, or delegate the computational tasks to the ground station. Informed decisions are based on low-latency computations of specific tasks without noticeable delay. Qian et al. [24] investigated the performance of a UAV-mounted mobile edge computing network where the UAV unit offloads and executes specific tasks that originate from some mobile terminal users. The trajectory planning problem was formulated as a Markov decision process (MDP) where optimal trajectories were obtained using a policy based on the double deep Q-network (DDQN) algorithm [25]. Thanks to the DDQN efficiency, higher throughput scores were attained.

A machine-learning-based solution for the planning of UAV trajectories is attributed to Afifi, and Gadallah [26]. Unlike many existing solutions, Afifi and Gadallah targeted missions with real-time navigation requirements in dense urban environments, where existing 5G infrastructures are astutely employed to ensure UAV navigation in complex environments through continuous interactions between the UAV units and the selected 5G network. Like [24], the proposed trajectory planning solution relies on deep reinforcement learning strategies, where the planning accuracy attains 99%.

In [27], Xia et al. proposed a flexible design of a wireless edge network using two UAV units. In this design, both units are restricted to operate at fixed altitudes with accelerated motions. Over a defined area, while the first UAV unit is in charge of forwarding downlink signals to the user terminals (UTs), the second unit is assigned to the collection of the uplink data. Using statistical information collected from the UT elements and UAVs, lower bounds on conditional average achievable rates are derived. The proposed scheme is demonstrated to attain an energy efficiency higher than existing ones.

Bin et al. [28] tackled the problem of the variability of user mobility and MEC environments, where they suggested a novel scheme for intelligent task offloading in UAV-enabled MEC systems using a digital twin (DT). At the core of the proposed scheme lies the DDQN model, which is specifically designed to effectively constrain multi-objective problems. The model was jointly optimized using closed-form and iterative procedures. The simulation results clearly indicate the convergence of the DDQN-based model while drastically minimizing the total energy consumption of the MEC system compared to existing optimization techniques.

A new aerial edge Internet of Things (EdgeIoT) system was contributed by Li et al. [29]. In this new EdgeIoT system, a UAV unit is operated as a mobile edge server for processing computational processes related to mission-critical tasks emanating from ground IoT devices. To capture the underlying feature correlations, a graph-based neural network architecture (GNN) was used for the supervised training of the A2C structure. The reported performance analysis highlights the superiority of the mixed GNN-A2C framework in terms of the convergence speed and missing task rates.

In [30], Qian et al. proposed a Monte Carlo tree search (MCTS)-based path planning technique assuming that a single UAV is deployed as a mobile service to provide computation tasks offloading services for a set of mobile users on the ground. The reported results show that the MCTS-based scheme outperforms state-of-the-art DQN-based planning algorithms in terms of the average throughput and convergence speed. In some instances, UAVs assist edge clouds (ECs) for the large-scale sparely distributed user equipment, which allows for wide coverage and reliable wireless communication. However, UAVs have limited computation and energy resources, which opens the floor for potential optimal resource allocation.

In [31], Wang et al. introduced a vehicular fog computing (VFC) system where unmanned ground vehicles (UGVs) perform the computation tasks offloaded from UAVs that are deployed in natural disaster areas. In these areas, UAVs are effectively used to survey disaster areas and even perform emergency missions, given their swift deployment and flexibility. However, this efficiency is hindered by the limited energy and computational capabilities of UAVs. These limitations are properly addressed by the VFC-based UAV system proposed by Wang et al., where UGVs may be assigned to perform the computation tasks offloaded from UAVs to save energy and computational power. To ensure a smooth and steady UAV–UGV collaboration and interaction, the computation task offloading problem was cast into a two-sided matching problem, where an iterative stable matching algorithm was used. This matching algorithm aims at assigning to each UAV the most suitable UGV among the available ones for offloading while maximizing the usage of both UAVs and UGVs and reducing the average delay.

Yang et al. [32] considered a UAV-enabled MEC platform where multiple mobile ground users move randomly and tasks arrive in a random fashion. To minimize the average weighted energy consumption of all users under constraints expressed in terms of data queue stability and average UAV energy consumption, Yang et al. suggested a multi-stage stochastic optimization scheme where Lyapunov optimization is converted into simpler per-slot deterministic problems vis-a-vis the number of optimizing variables. Based on their formulation, Yang et al. solved the resource allocation and the UAV movement problems using two reduced-complexity methods, either jointly or separately. The two methods not only satisfy the average UAV energy and queue stability constraints, but they also reconcile the length of the queue backlog and the user energy consumption bounds. The reported results show that the proposed joint and two-stage stochastic optimization schemes outperform existing learning-based solutions. Finally, it should be noted that the joint optimization scheme attains a better performance than its two-stage counterpart at the expense of an increased computational complexity. Most of the solutions discussed so far attempt to optimize the UAVs' total (or average) energy consumption and computational power allocation among mobile users using some type of learning-based strategy.

In their proposal, Lyi et al. [33] adopted a different approach to maximize the computation bits of the whole MEC system: the joint optimization of task offloading time allocation, bandwidth allocation, and the UAV trajectory under specific energy constraints of ground devices and maximal UAV battery energy. The proposed solution splits the overall optimization procedure into three stages, where successive convex optimization schemes are used. Once individual solutions are identified, a block coordinate descent (BCD) algorithm integrates the solution of the initial optimization problem. Such a formulation aims at obtaining alternating optimal solutions for the optimization variables considered (bandwidth allocation of ground devices, task offloading time, local computing time allocation, and UAV trajectory) at each time slot. Extensive simulation experiments were conducted to demonstrate the performance improvement attained by the proposed BCD-based solution.

Overall, the proposed solutions discussed in this section suggest that UAV-based edge computing systems have certain advantages over cloud-based techniques in terms of optimization, convergence speed, throughput, and energy efficiency. These advantages make UAV-based edge computing systems a promising solution for various applications, including precision agriculture, smart cities, and disaster management, where real-time data processing and optimization are critical.

1.3.2. Summary of Related Works

A summary of the current literature is provided in Table 1. Onboard AI edge computing is becoming increasingly important for UAV systems, especially those utilizing EMC-based solutions. While EMC-based UAV systems offer benefits such as flexibility, resilience, and swift deployment, they also present new challenges that can only be addressed by advanced AI-based solutions, such as reinforcement and deep learning frameworks.

One reason for why onboard AI edge computing is necessary for EMC-based UAV systems is the need for real-time decision making. In certain applications, such as emergency response, decisions need to be made quickly and accurately. Onboard AI edge computing can process data in real time, allowing the UAV to make decisions based on the information that it collects, without the need for remote servers. This reduces latency and ensures that decisions are made in a timely manner.

On the other hand, Table 6 summarizes the obtained results when using the PyTorch or the TRT implementations of the YOLOv7 object detector on video 4. The difference between the two implementations is relatively minor, except for identity switches, which double from 5 to 10 when converting the PyTorch model to TRT. This indicates a loss in precision in the converted detection model that impacts the tracker accuracy. Nevertheless, this figure remains relatively low (1.6% to 3.1% relative to the number of frames) considering the number of cars and the duration of the video. By contrast, the number of identity changes is much higher, both for the PyTorch and the TRT implementations. The tradeoff between the number of identity switches and identity changes can be modified by changing the tracker hyperparameters, but we consider the identity switches to be more critical because they entail the conflation of the information of different objects, whereas the identity changes only result in duplicate information sent to the server. On the other hand, we observe that the number of false negatives is much higher than the number of false positives. In fact, small or occluded objects are often missed by the object detector, as can be seen in Figure 5. Consequently, the precision is high (99.3% for both PyTorch and TRT implementations), whereas the recall is much lower (72.5% and 73.1% for PyTorch and TRT, respectively). This tradeoff can also be modified by changing the score threshold for the object detector.

Table 5. Number of false positive detections (FPs), false negative detections (FNs), precision, recall, F1 score, identity switches, and identity changes for the TRT implementation of the YOLOv4 object detection model on test video 1 (resolution of 3840 × 2160, length of 50 s, FPS of 30) captured by a drone, showing 6 classes (car, person, bicycle, bus, monocycle, and truck).

	FP	**FN**	**Precision**	**Recall**	**F1 Score**	**Identity Switches**	**Identity Changes**
YOLOv4 TRT	80	33	82.7%	92.1%	87.1%	16	26

Table 6. Number of false positive detections (FPs), false negative detections (FNs), precision, recall, F1 score, identity switches, and identity changes for the PyTorch and TRT implementation of the YOLOv7 object detection model on test video 4 (resolution of 1920 × 1080, length of 4 mn and 25 s, FPS of 24) captured by a drone, showing a single class of 'cars'.

	FP	**FN**	**Precision**	**Recall**	**F1 Score**	**Identity Switches**	**Identity Changes**
YOLOv7 PyTorch	20	1136	99.3%	72.5%	83.8%	5	184
YOLOv7 TRT	22	1099	99.3%	73.1%	84.2%	10	176

5. Conclusions

The commercial usage of UAVs is still largely limited by the lack of onboard AI on the edge, leading to manual data observation and offline processing after data collection. Alternatively, some approaches rely on the cloud computation offloading of AI applications, which can be unscalable and infeasible due to a limited connectivity and high latency of remote cloud servers. To address these issues, in this paper, we proposed a new approach that uses edge computing in drones to enable extensive AI task processing on board UAVs for remote sensing applications. The proposed system architecture involves a cloud–edge hybrid approach where the edge is responsible for processing AI tasks and the cloud is responsible for data storage, manipulation, and visualization.

To implement this architecture, coined AERO, we designed a UAV brain system with onboard AI capabilities that uses GPU-enabled edge devices. AERO is a novel multi-stage deep learning module that combines object detection (YOLOv4 and YOLOv7) and tracking (DeepSort) with TensorRT accelerators to capture objects of interest with a high accuracy and transmit data to the cloud in real time without redundancy. AERO processes the detected objects over multiple consecutive frames to maximize detection accuracy. The experiments show that the proposed approach is effective for utilizing UAVs equipped with onboard AI capabilities for remote sensing applications.

While the proposed system architecture and AERO module were designed to process visual data from UAVs, future work could explore the integration of other sensors, such as LiDAR or thermal cameras, to enhance the accuracy and efficiency of remote sensing applications. In addition, we plan to explore the integration of autonomous navigation capabilities to enable UAVs to navigate and collect data independently, without the need for manual control or intervention.

Another crucial aspect that needs to be considered in future works when designing drone systems with onboard AI capabilities is security, as highlighted in [46–48] . Drone communications are susceptible to cyber-attacks, making it crucial to protect the data being transmitted between the UAV and the cloud. Implementing security measures such as encryption and authentication protocols can protect the system from unauthorized access and data breaches. Additionally, implementing physical security measures such as tamper-proofing the onboard AI hardware can prevent malicious actors from tampering with the system. These security measures must be implemented at every stage of the system development and deployment to ensure the safety and privacy of data collected by UAVs. Nevertheless, these measures can affect the system's inference speed in a way that still has to be investigated.

Author Contributions: Conceptualization, A.K. and A.A.; methodology, A.K., A.A. and M.A.; software, Y.A. and A.A.; validation, A.K., A.A. and M.A.; formal analysis, A.K., A.A. and M.A.; investigation, A.K., A.A. and M.A.; resources, A.K.; data curation, A.A. and Y.A.; writing—original draft preparation, A.K., A.A., M.A. and L.G.; writing—review and editing, A.K., A.A., M.A. and L.G.; visualization, A.A. and M.A.; supervision, A.K., A.A. and M.A.; project administration, A.K.; funding acquisition, A.K. All authors have read and agreed to the published version of the manuscript.

Funding: The APC for this article was funded by Prince Sultan University.

Acknowledgments: We thank Prince Sultan University for facilitating the experiments on the university campus and financially supporting publication expenses.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results

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