Learning IoV in 6G: Intelligent Edge Computing for Internet of Vehicles in 6G Wireless Communications

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Learning IoV in 6G: Intelligent Edge Computing for Internet of Vehicles in 6G Wireless Communications

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***Abstract*—In sixth-generation (6G) wireless communications, deep learning will still be essential for the Internet of Vehicles (IoV). 6G will bring new opportunities and challenges to current deep learning systems applied in the IoV environment. This article introduces a new framework named Learning IoV in 6G, focusing on the deep learning applications for IoV in 6G. We also apply the proposed framework in a flying base station (FBS) to evaluate the performance for future IoV in 6G.**

I. Introduction

Internet of Vehicles (IoV) is an emerging technology to orchestrate vehicle to vehicle (V2V), vehicle to infrastructure (V2I), vehicle to human (V2H), and vehicle to sensor (V2S) for building next-generation intelligent transportation systems (ITS). In IoV, as the fundamental of artificial intelligence (AI) applications, deep learning technologies will play a critical role in many applications such as autonomous driving, intelligent traffic control, and usage-based insurance. In addition, existing vehicle manufacturers have begun to add additional computing facilities in high-end models to support deep learning processing [1].

However, there are still several challenges to applying deep learning-based applications in existing IoV environments. The first challenge is the limited network coverage even with 5G wireless communications, which are still based on deploying a large number of base stations (BSs). Without enough network coverage, it is not easy to maintain continuous services during driving vehicles in sparsely populated areas [2].

The second challenge is applying more complex applications on limited hardware platforms. It is challenging to replace the computing facilities in vehicles after leaving the factory. Meanwhile, car facilities are not appropriate for external applications due to the high-security requirement. Also, it is almost impossible to share the processing resources between different vehicles.

The sixth-generation (6G) communications will make huge progress on the network coverage due to the application of low earth orbit (LEO) and very low earth orbit (VLEO) satellites. It is easy to cover global areas without building base stations on the ground. During the next decade, some providers such as SpaceX and OneWeb will construct several satellite constellations with thousands of or more satellites covering all over the earth. It is possible to develop global IoV applications without considering network access. Moreover, for covering obscured areas (e.g., in tunnels, under viaducts, etc.) or dense areas, 6G introduces movable BSs such as flying BSs (FBSs) or autonomous vehicle-mounted BSs to support flexible network coverage [3].

Intelligent edge computing is another opportunity for supporting deep learning applications in IoV environments. Since more and more edge devices of mobile networks have enough computation capability to process deep learning tasks, deploying AI applications in edge becomes possible, especially in future 6G wireless communications. Thus, instead of vehicle facilities, edge servers will play a major role in supporting future deep learning-based applications in IoV environments [4], [5].

In this article, we survey some related literature and then introduce the possible scenario of IoV in future 6G wireless communications. The LEO and VLEO satellite-based wireless networks will work as the primary access networks for IoV devices, and as the complement, autonomous movable BSs help the vehicles in obscured or dense areas connect to the mobile network. Based on the 6G network structure, we discuss intelligent edge computing for processing deep learning tasks with sensing data from vehicles and other sensors [6].

We also design and implement an unmanned aerial vehicle (UAV) based prototype as FBS to illustrate the efficiency of intelligent edge computing for IoV. The prototype offloads the deep learning tasks from the cloud to the onboard computer deployed on the UAV, reducing network latency and overload during executing AI applications. The performance evaluation results show the prototype outperforms the cloud-based deep learning structure [7].

The remainder of this article can be outlined as follows. The next section introduces 6G communications and intelligent edge computing for IoV. Following are the deep learning scenario for IoV in 6G and the design of the FBS prototype. Finally, the fifth section presents the evaluation results of the prototype in processing deep learning tasks, followed by the conclusions drawn in the last section.

II. Related Work

This section studies some related literature about 6G and intelligent edge computing for IoV.

A. 6G and IoV

The fifth-generation (5G) wireless communications will be deployed in most areas in the next decade. In the 6G Era,

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current research works have already paid much attention to the cross-field with UAV, Satellite, Internet of Vehicles, etc. Nikooroo et al. regard UAVs as flying base stations in assisting 6G communications in mobile networks. Their research focuses on how to allocate the power carried by UAVs to users in need while considering the movement of both sides [3]. Satellite communications will be the most crucial part of 6G in the next decade to connect the uncovered areas on the earth. Some initial systems, such as O3b, Starlink, Lightspeed, and Kuiper, have provided basic network access services to general customers. However, satellite communications need special hardware to bridge satellites and ground end devices. However, since the satellite communication devices are heavy and energy consuming, applying airborne devices to bridge ground vehicles and satellite is appropriate. Huang et al. propose an integrated space and terrestrial network architecture in which UAVs and other aircraft form an airborne tier between ground networks and satellites. In this way, Geostationary Earth Orbit (GEO), Medium Earth Orbit (MEO), and Low Earth Orbit (LEO) satellites can build a connection with users at the ground through this airborne tier [6]. Nawaz et al. summarize the state-of-the-art technologies that appeared from Beyond 5G (B5G) to 6G. UAVs and satellites separately play the role of a mobile base station, and mmWave communication provider [5]. Zhao et al. design an intelligent reflecting surface architecture to reduce extra energy consumption and increasing the spectrum of 6G communication among smart devices, including UAVs and vehicles [2]. Tariq et al. study the possible technologies that may become a hotspot soon. In the comparison between the upcoming 5G, they point out that with 6G, we can build a service-centric reliable real-time architecture to satisfy pervasive cases, including ultra-sensitive applications, satellite integration, autonomous vehicle-to-everything (V2X), and so on [8].

B. Intelligent Edge Computing

Edge computing shows its efficiency in offloading computing from cloud to edge. As a result, the network traffic can be reduced since it is not needed to transfer most data to the cloud. Intelligent edge computing is a specific edge computing model focusing on offloading AI or machine learning tasks to edge. Therefore, we discuss several related works optimizing the offloading convolutional neural networks (CNN) network into edge servers. In the first work, we find that intermedia data after processing by the first several layers is much smaller than the input data. In the second work, we introduce deep reinforcement learning to improve the resource scheduling of the edge or fog servers.

Existed works on Edge AI have already paid attention to many related fields, including IoT, mobile edge computing, smart traffic, and blockchain. Zhou et al. survey the possible recent research findings in the field of edge intelligence, which include the up-to-date key technologies, architectures, and so on [1]. Chen et al. propose a label-less learning approach to solving the traffic flow control problem in the edge-cloud network. In their design, we can intelligently allocate available computing resources in traffic operations to meet the demand from self-driving and other real-time applications [7]. Zhou et al. discuss the possibility of allocating the inference computation of all network layers to devices in artificial intelligence IoT systems [9]. Zhu et al. focus on the concepts of edge learning and learning-driven communication and solve the trade-off between learning at the edge and edge-cloud communications [10]. Wang et al. design an In-Edge AI framework to enhance federated learning by decreasing extra system communication workload in mobile edge computing [4]. Lin et al. introduce blockchain in establishing a peer-to-peer knowledge trading framework in edge AI-enabled IoT networks [11]. Moreover, intelligent edge computing has become a promising technology to support different AI applications. For example, Yang et al. propose an intelligent edge architecture for 6G networks to support advanced network services, such as automatic and delicate resource management and network adjustment [12]. Meanwhile, since providing various intelligent services will be a strong demand in the future, intelligent edge computing will be an indispensable part of 6G communications.

III. Learning IoV in 6G

In this section, the scenario of deep learning for IoV in 6G is discussed, and we also give some major challenges for deep learning tasks in IoV.

A. Scenario of Learning IoV in 6G

We use a small example to illustrate the scenario of IoV in 6G wireless communications. As shown in Fig. 1, there are three distinct layers in the IoV in 6G, the vehicle layer, the FBS layer, and the Satellite layer. Usually, the vehicle layer consists of various vehicles connected by vehicle-to-vehicle (V2V) communications. The link between two vehicles in one hop has very high bandwidth and very low latency, which is not stable due to the movement of vehicles on the road. Meanwhile, a vehicle in the vehicle layer can connect to an FBS, and when there is no nearby vehicle, each vehicle will connect to an FBS for the network connection.

UAVs connect vehicles and satellites in the FBS layer as the network bridge. A UAV also plays a role like a roadside unit (RSU) in a classic vehicle to infrastructure (V2I) network to connect vehicles in the communication area. Since the communication area is larger than an FBS, the link between a UAV and a satellite is stabler than a vehicle.

In the satellite layer, links between LEO/VLEO satellites usually have large bandwidth and acceptable latency due to the line of sight (LOS) communications with very high frequency. For example, in Starlink satellite, links between satellites will be built by laser communications with 193-Thz frequency to provide a bandwidth of up to 10 Gbps [13]. Meanwhile, a ground terminal needs a large antenna to receive and send signals to satellites due to the long distance between satellites and the ground. Therefore, we assume that only the FBS layer and satellite ground stations can communicate with satellites directly in the scenario.

When a deep learning task is deployed for the IoV environment, vehicles send the data to a processor for further processing. Since most deep learning-based processes need very high computing capability, a high-end cloud server will usually process the input data and send back results to vehicles. As a result, in the above scenario, the data will be sent from the vehicle layer, across the FBS and satellite layers, to a cloud data center on the ground.

B. Challenges of Learning IoV in 6G

Based on the procedures of executing a deep learning task in the IoV and 6G environment, the following challenges limit the quality of service (QoS) or the quality of experience (QoE).

The first challenge is the high latency in real-time processing tasks. The latency mainly consists of transferred, propagation, and processing. Propagation latency will be very long in processing a deep learning task in satellite communications. One hop in satellite communications will be near 100 ms, while there are at least six hops in processing procedures even without the FBS layer, including the hops between the vehicles and satellite layer, between satellites, and between the satellite layer and the ground station. The time for processing a deep learning task is also significant for the real-time requirement. For example, the processing time from a target recognition task usually needs tens of milliseconds with a typical embedded processor. Therefore, processing real-time tasks is complicated in the satellite communication environment.

The second challenge is the bandwidth bottleneck between the vehicle and the satellite layers. Due to the high bandwidth requirement for transferring high-quality video streams, dense areas with many vehicles will lead to congestion in uploading data to satellites. Although existing video coding methods show enough efficiency to reduce the video size, the much higher resolution of future video sensing data will still be a challenge to the uplink from the vehicle to the satellite.

The third challenge is the high cost of transferring data in providing IoV services. Although the providers try to reduce the cost of satellite communications, a large amount of data transferring will lead to a unfadeable price of AI-based IoV services. In a VLEO satellite system, satellites need fuel to maintain their orbit because of the aerodynamic drag. Therefore, the maintenance cost of VLEO satellite systems will be higher than traditional LEO systems for providing mobile network access.

The fourth challenge is maintaining stable links between the satellite and UAVs, especially in the communications with LEO and VLEO systems. Usually, an LEO satellite is only visible to a UAV for 2 to 20 minutes, while it becomes worse with VLEO satellites. Therefore, since an LEO or VLEO satellite can cover a large area, processing all handover requests from many UAVs is very challenging.

It is necessary to introduce a new model to face the above challenges. We will introduce intelligent edge computing in the next section and show its opportunity to process deep learning tasks with 6G networks.

IV. Intelligent Edge Computing for IoV in 6G

In this section, we will first introduce the model of intelligent edge computing and then present the design of our prototype.

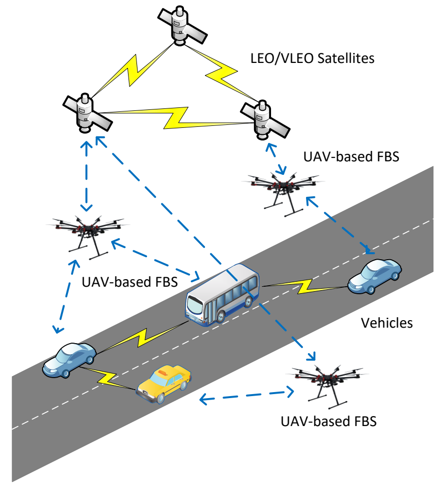


Fig. 1. Scenario of IoV in a possible 6G communication network

A. Intelligent Edge Computing in 6G

Since the challenges of processing deep learning tasks come from extensive data transferring, edge computing will be an opportunity to reduce uploading data with the offloading strategy. Considering that only a part of the video sensing data is applied in IoV services, extracting useful information before uploading is possible and necessary. Intelligent edge computing is a specific edge model focused on the learning phase of data processing. Because the vehicle manufacturers will not open the access right of vehicle computers to IoV service providers, intelligent edge computing will mainly depend on the edge servers deployed in the FBS and satellite layers.

We discuss a typical methodology for processing deep learning tasks. When a vehicle records a video or a photo, all sensing data will be sent to the FBS layer first if BSs exist near vehicles. Then, most BSs will have edge servers to process the received data. The processing procedures depend on the neural network structures in deep learning tasks. Since the neural networks become more and more complex, edge servers will only process a part of layers due to the limited computing capacity. Even if only several layers are deployed in the edge server, the sensing data will shrink sharply after processing.

However, the propagation latency is hard to reduce if edge servers in the FBS layer only process a part of a neural layer of each task. Therefore, it is also needed to deploy enough computing power in the satellite layer to process tasks and return the results to vehicles or mobile users. The edge servers in the satellite layer will be more powerful since satellites' size and energy supplement are adequate than FBSs. Meanwhile, it is also possible to build a distributed computing model with tens or hundreds of satellites in the near area.

Even if there is still a part of the data needed by the cloud server, the upload bottleneck and transferring cost are much reduced by the intelligent edge computing model. Meanwhile, another solution is deployed to multiple networks with differ-

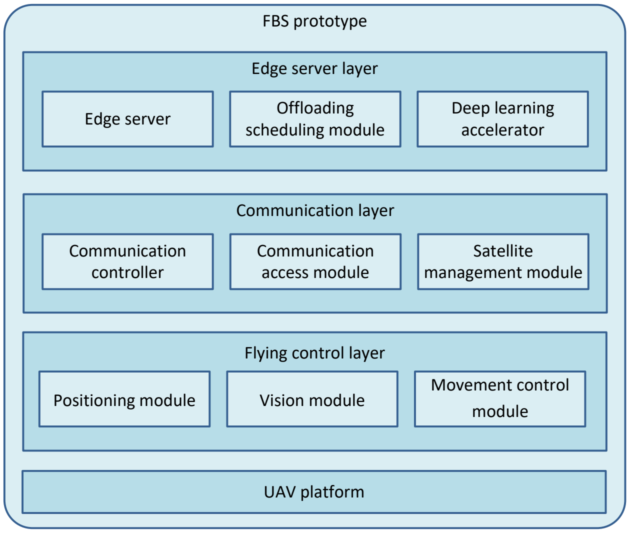


Fig. 2. Main modules in the FBS prototype

ent depths. A simple neural network will generate initial results from the sensing data to vehicles, which can be fully deployed in the FBS layer. A deeper neural network will be deployed in the BS and satellite layers, while the deepest network will be deployed in the entire transferring procedure and the cloud server. If users need low latency real-time services, a BS will return the result in tens of or several milliseconds. While a more detailed or specified result is required, the entire response time will be hundreds of or more seconds.

As a result, intelligent edge computing will be an emerging mode to face the challenges form learning IoV in 6G. The deep learning specific offloading strategy and multiple networks at different depths reduce the transferring data and response latency.

B. FBS Prototype Design

We also propose an FBS prototype to offload deep learning tasks for IoV in future 6G networks. As shown in Fig. 2, except for the mechanical part, the entire FBS prototype has three layers: the flying control, the communication, and the edge server.

There are three major modules in the flying control layer: the positioning module, the vision module, and the movement control module. The positioning module measures the real-time altitude, longitude, and latitude information. The vision module recognizes the object in the video or radar sensors. The movement control module moves the UAV to an appropriate position based on the location information, surrounding environment, and vehicle distribution. Meanwhile, upper layers will also interact with the flying control layer to adjust the position according to the network status or offloading requirement.

Since details of 6G protocols are not yet proposed in the communication layer, we assume there are at least three modules, the communication controller, the communication access, and the satellite management module. The communication controller controls and monitors the network access status and sends requirements to the flying control layer for position adjustment. The communication access module connects the satellites and vehicles through different interfaces. The satellite management module organizes the locations of satellites and handovers in satellite communications.

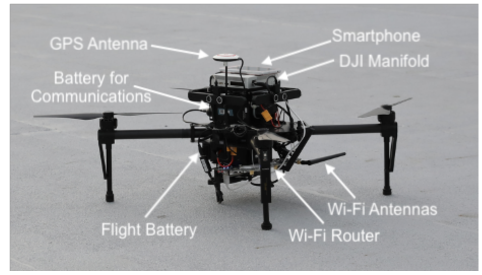


Fig. 3. Testbed of the FBS prototype with a DJI Matrice 100 platform

The edge server layer consists of an edge server, an offloading scheduling module, and a deep learning accelerator. The edge server will have an isolation mechanism to separate different tasks. For example, lightweight virtualization (Infrastructure as a Service) or a docker system (Platform as a Service) will be applied in future edge servers. The offloading scheduling module will estimate the QoS and QoE of the offloading decision of each task and assign the rest of the computing resources. The deep learning accelerator manages specific hardware and lightweight frameworks for accelerating deep learning tasks. In the future, specially-designed application-specific integrated circuit (ASIC) chips will play an essential role in supporting intelligent vehicle services.

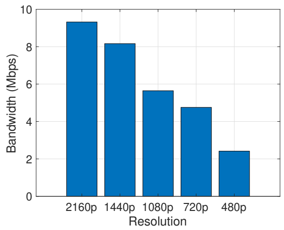
When the IoV provider wants to deploy an AI service in the 6G network, it needs to apply edge resources according to the expected coverage area, required computing power, and QoS or QoE demand. After that, the carrier will assign the required edge resources in the satellite and FBS layers. The maximum size of the assigned docker or virtual machine can reflect the required resources. After deployment, the FBS receives the sensing data from vehicles. The flying control layer will move the UAV to an appropriate position calculated by communications requirements and offloading of vehicles. When the FBS receives sensing data from vehicles, the offloading layer will offload proper computing in the corresponding docker or virtual machine. After processing in the edge server, the FBS will simultaneously send the initial result to vehicles and cloud services. In the next section, we will test the efficiency of the prototype design with a UAV and a deep learning oriented onboard computer.

V. FBS Prototype Evaluation

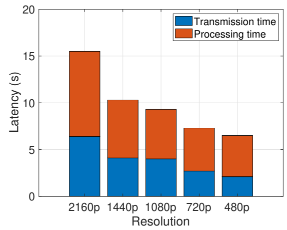
We test the performance of the FBS prototype on a testbed and then evaluate the scalability of the FBS prototype with extensive simulations.

A. Testbed Experiments

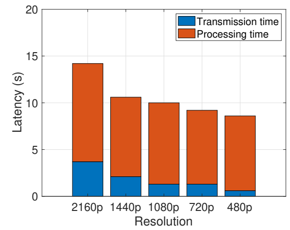
The FBS prototype testbed shown in Fig. 3 is developed with a DJI Matrice 100 platform, a quadcopter for develop-



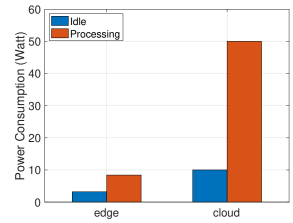
(a) Upload bandwidth with cloud



(b) Latency with cloud

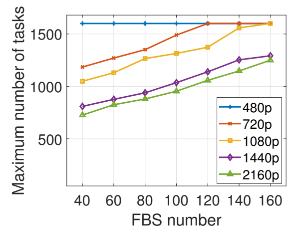


(c) Latency with edge

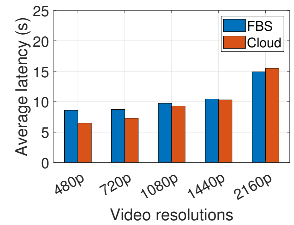


(d) Power consumption

Fig. 4. Experiment results on the FBS prototype testbed



(a) Number of tasks



(b) Average latency

Fig. 5. Simulation results with the FBS prototype

ment. On the Matrice 100, we mount an ASUS RT-AC68U Wi-Fi router as the access point and an AQUOS SERIE SHV32 smartphone for LTE access. As the edge server on the UAV, we also install a DJI Manifold onboard computer that has an NVIDIA Tegra K1 system on a chip (SoC), 2GB DDR3L system RAM, and 16 GB eMMC 4.51 storage. Since the Tegra K1 SoC includes an NVIDIA GPU consisting of 192 ALUs, the edge server can process lightweight deep learning tasks. We use a Google Pixel 3A XL smartphone as the video sensor.

We install an Ubuntu 14.04 LTS as the operating system in Manifold. We use the CUDA L4T r21.3 package to process deep learning tasks. We use Darknet as the neural network framework and apply tiny-YOLO to detect objects in video data from the video sensor [14]. Since the prototype focuses on the tasks in the inference phase, we only test the inference performance with a pretrained tiny-YOLO model. The model is trained by the COCO dataset, with more than 200,000 images and 80 object categories. The mean average precision of tiny-YOLO is near 24.

We prepared five 30-second videos with different resolutions as input for object detection in all experiments. The resolutions are 480p (720x480), 720p (1280x720), 1080p (1920x1080), 1440p (2560x1440) and 2160p (3840x2160). As a comparison, we apply a server with an Intel core i9 10850k CPU and 64 GB memory. The operating system on the server is Ubuntu 16.04 LTS, and its CUDA version is 10.0.

The bandwidth overhead for real-time processing tasks in the cloud server is first recorded in Fig. 4(a). From the bandwidth record, for transferring the 4k video to the cloud, it needs near 10 Mbps uplink bandwidth. A 5G base station can only support uploading no more than 100 videos simultaneously. As an available satellite system in the next decade, Starlink only has 610 Mbps bandwidth. Thus, processing high-resolution video data recorded by vehicles by the cloud is still a challenge to future communication systems. Offloading deep learning tasks from cloud to edge is an emerging technology for supporting future IoV services.

We then test the latency in processing the five videos. The latency mainly includes transmission time and processing time. As shown in Fig. 4(b) and 4(c), we compare the latency of processing five videos on the edge and the cloud server. Due to the Tegra K1 SoC limitation, the processing time on the cloud server is shorter than the time on the edge. The transmission time is reduced significantly by the edge computing model, especially in high-resolution transfer videos. Considering the DJI Manifold is a model released three years ago, the new edge hardware will dramatically improve the performance of processing AI-based tasks.

Moreover, we test the power consumption of the testbed and the cloud server for processing the task. The edge device consumes 3.2 Watts of power in the idle status, while the cloud server needs more than 10 Watts. The edge device needs 8.7 Watts of power to process the task, while the cloud server consumes more than 50 Watts.

B. Large Scale Simulations

For evaluating the scalability of the proposed FBS prototype, we also take extensive simulations in a road environment. We use SUMO to generate a 10×10 traffic grid, and each road connecting two adjacent intersections is set to be 100 meters. Up to 180 vehicles are on the map with an average speed of 10 m/s. The communication range of an FBS is set to 200 meters, and the bandwidth between vehicles and an FBS is 600 Mbps. For covering the entire map, the number of FBS is set from 40 to 160. The satellite aggregated uplink bandwidth is set to 610 Mbps from Starlink. The average latency with edge and cloud is set as the results in Fig. 4(b) and 4(c). We record the positions of each vehicle in each second and import the position data into the simulator developed by Matlab 2019b. Each test is taken 20 times, and we record the average results.

As shown in Fig. 5, we set the number of FBSs from 40 to 160 for serving vehicles for network communications and real-time object recognition tasks. We first test the maximum service capability of a real-time object recognition task and set the video resolutions from 480p to 2160p. From the result of the testbed experiments, an FBS can simultaneously process five real-time video streams. From Fig. 5(a), we record the maximum number of tasks with different resolutions from 480p to 2160p. Service capability is limited when the resolution is 480p because of the low bandwidth requirement for transferring low-bitrate videos. When processing high-resolution videos, the number of tasks is limited by the uplink bandwidth of the satellite communication. Increasing the number of FBSs can improve the system capability since edge servers offload tasks from the cloud server. When the number of FBSs is set to 160, the system can process more than 600 videos, nearly twice the number with 5 FBSs.

As shown in Fig. 5(b), we compare the average latency with the prototype and cloud-based solution. We set the number of tasks to 1600, which is the maximum service capacity of the given settings. We assume the cloud will handle tasks that the FBS does not process. The number of FBS is set to 40. Although the performance of the Jetson K1 platform is very weak, the average latency with FBS is still better than the cloud-based solution when the video resolution is set to 2160p. As a result, the FBS prototype will improve the service capability and reduce the average latency of the deep learning tasks for IoV in 6G wireless communications.

VI. Conclusion and Future Work

Intelligent edge computing will improve the efficiency of deep learning tasks for IoV in wireless communications. When satellite communications are applied in future 6G networks, the intelligent edge in FBSs will be an emerging technology for future AI-based IoV applications. Our FBS prototype shows preliminary results for accelerating deep learning tasks in mobile networks. In the future, a meaningful way to improve the efficiency of the FBS prototype is to apply a new DJI Manifold computer, and we also plan to design a new edge-oriented deep learning framework.

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References

[1] Z. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, and J. Zhang, "Edge intelligence: Paving the last mile of artificial intelligence with edge computing," *Proceedings of the IEEE*, vol. 107, no. 8, pp. 1738–1762, aug 2019.

[2] J. Zhao, "A survey of intelligent reflecting surfaces (IRSs): Towards 6g wireless communication networks," 2019.

[3] M. Nikooroo and Z. Becvar, "Joint positioning of UAV and power control for flying base stations in mobile networks," in *2019 International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. IEEE, oct 2019.

[4] X. Wang, Y. Han, C. Wang, Q. Zhao, X. Chen, and M. Chen, "In-edge AI: Intelligentizing mobile edge computing, caching and communication by federated learning," *IEEE Network*, vol. 33, no. 5, pp. 156–165, sep 2019.

[5] S. J. Nawaz, S. K. Sharma, S. Wyne, M. N. Patwary, and M. Asaduzzaman, "Quantum machine learning for 6g communication networks: State-of-the-art and vision for the future," *IEEE Access*, vol. 7, pp. 46 317–46 350, 2019.

[6] X. Huang, J. A. Zhang, R. P. Liu, Y. J. Guo, and L. Hanzo, "Airplane-aided integrated networking for 6g wireless: Will it work?" *IEEE Vehicular Technology Magazine*, vol. 14, no. 3, pp. 84–91, sep 2019.

[7] M. Chen, Y. Hao, K. Lin, Z. Yuan, and L. Hu, "Label-less learning for traffic control in an edge network," *IEEE Network*, vol. 32, no. 6, pp. 8–14, nov 2018.

[8] F. Tariq, M. R. A. Khandaker, K.-K. Wong, M. A. Imran, M. Bennis, and M. Debbah, "A speculative study on 6g," *IEEE Wireless Communications*, vol. 27, no. 4, pp. 118–125, aug 2020.

[9] J. Zhou, Y. Wang, K. Ota, and M. Dong, "AAIoT: Accelerating artificial intelligence in IoT systems," *IEEE Wireless Communications Letters*, vol. 8, no. 3, pp. 825–828, jun 2019.

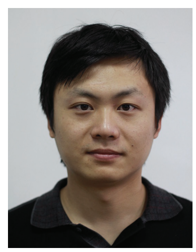
[10] G. Zhu, D. Liu, Y. Du, C. You, J. Zhang, and K. Huang, "Toward an intelligent edge: Wireless communication meets machine learning," *IEEE Communications Magazine*, vol. 58, no. 1, pp. 19–25, jan 2020.

[11] X. Lin, J. Li, J. Wu, H. Liang, and W. Yang, "Making knowledge tradable in edge-AI enabled IoT: A consortium blockchain-based efficient and incentive approach," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 12, pp. 6367–6378, dec 2019.

[12] H. Yang, A. Alphones, Z. Xiong, D. Niyato, J. Zhao, and K. Wu, "Artificial-intelligence-enabled intelligent 6g networks," *IEEE Network*, vol. 34, no. 6, pp. 272–280, 2020.

[13] A. U. Chaudhry and H. Yanikomeroglu, "Laser intersatellite links in a starlink constellation: A classification and analysis," *IEEE Vehicular Technology Magazine*, vol. 16, no. 2, pp. 48–56, jun 2021.

[14] J. Redmon and A. Farhadi, "Yolov3: An incremental improvement," Apr. 2018.



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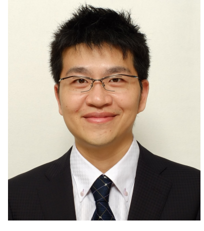


Mianxiong Dong is the Vice President and Professor at Muroran Institute of Technology. His research interests include large-scale network systems such as mobile networks, wireless sensor networks, vehicle networks, cyber-physical systems, and IoT. He is also engaged in research on a wide range of cutting-edge information technologies, such as edge computing, AI technology, SDN, and big data analysis. His laboratory combines knowledge in the field of large-scale network systems with physical layer technologies to create new value.

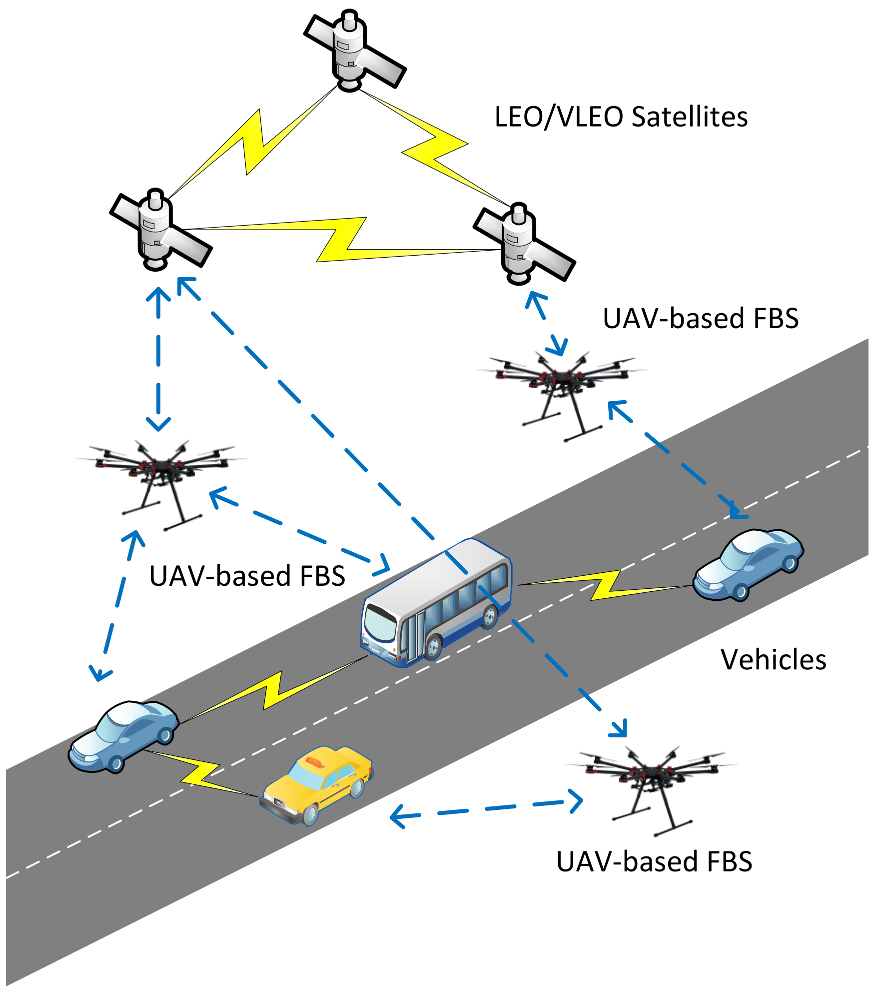


Fig. 1. Scenario of IoV in a possible 6G communication network

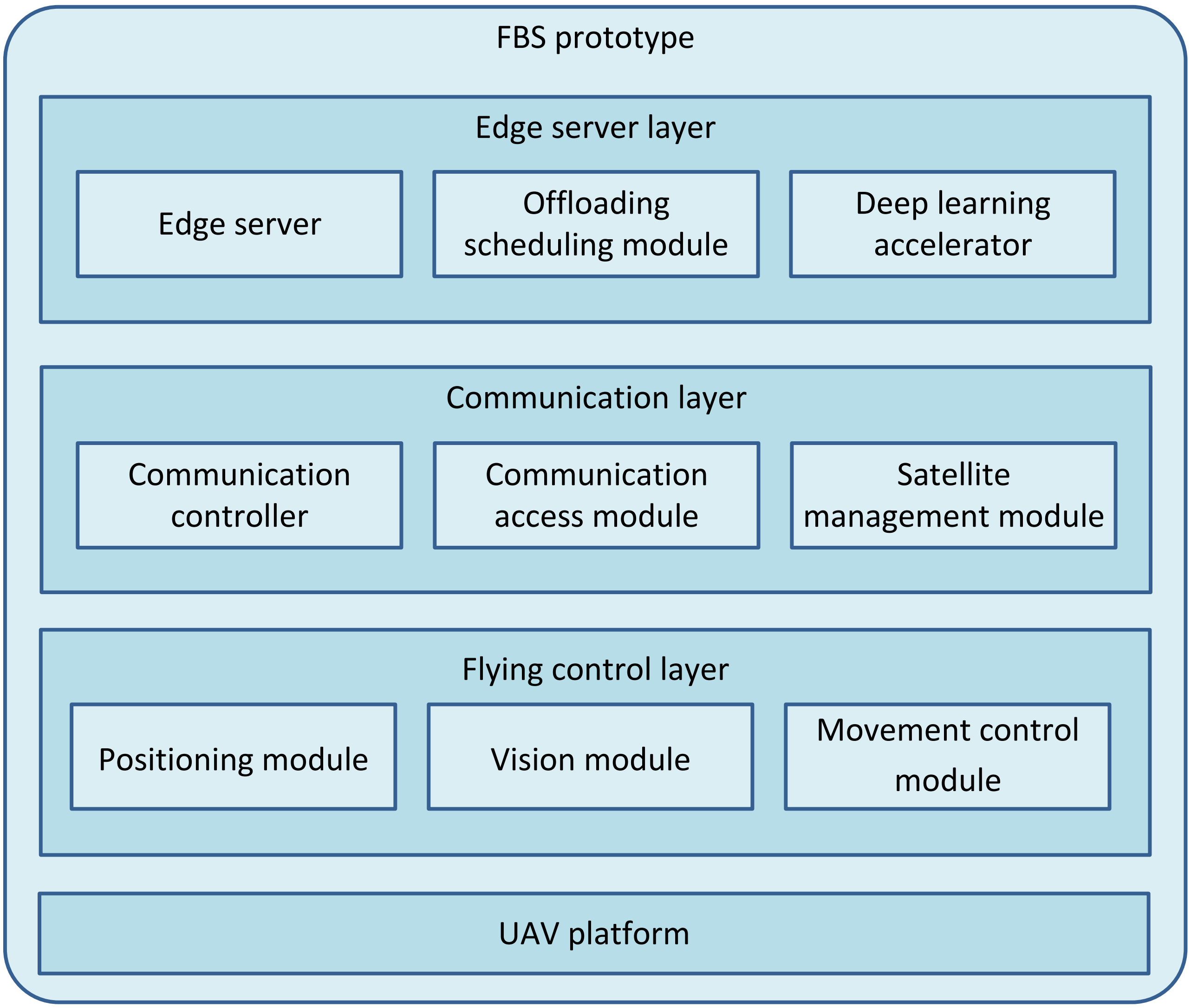


Fig. 2. Main modules in the FBS prototype

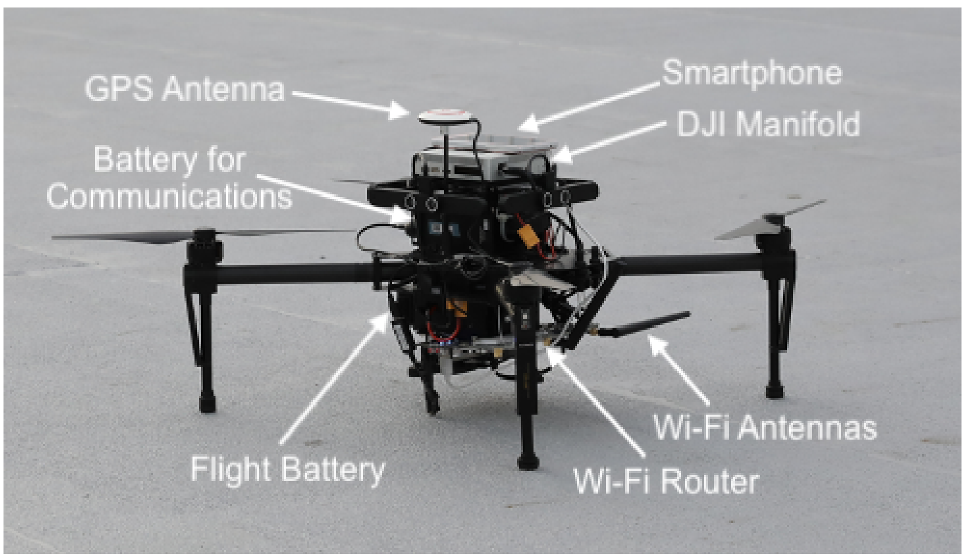
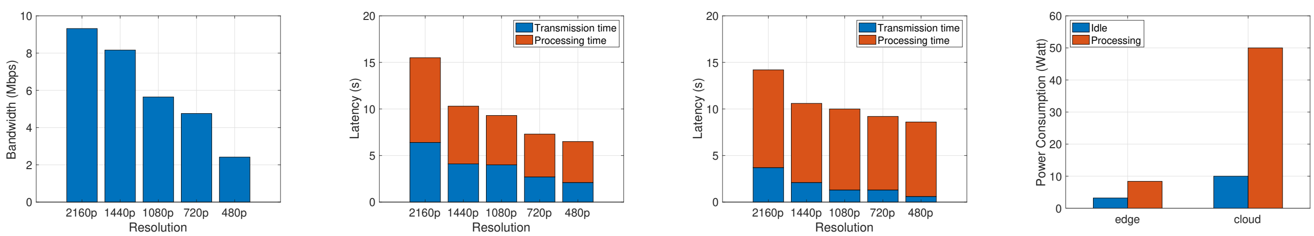


Fig. 3. Testbed of the FBS prototype with a DJI Matrice 100 platform



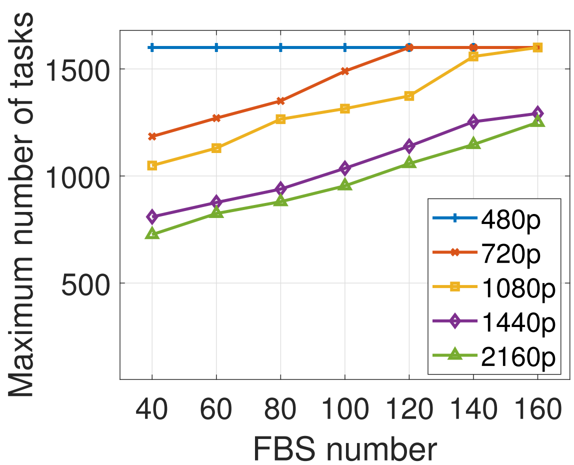
(a) Upload bandwidth with cloud

(b) Latency with cloud

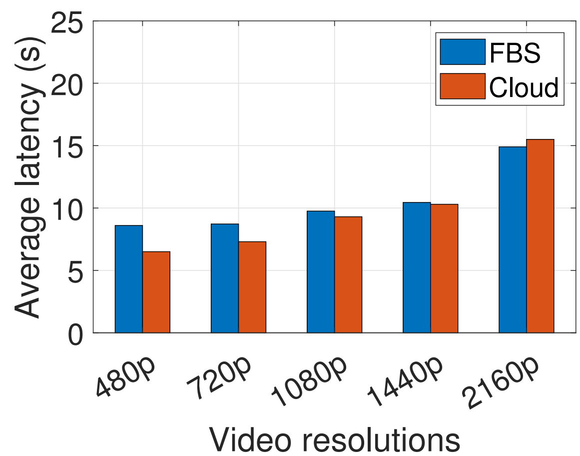
(c) Latency with edge

(d) Power consumption

Fig. 4. Experiment results on the FBS prototype testbed



(a) Number of tasks



(b) Average latency

Fig. 5. Simulation results with the FBS prototype