Edge Computing Empowered Generative Adversarial Networks for Realtime Road Sensing

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I. Introduction

Automobiles have become one of the necessities of modern life and deeply penetrated into our daily activities. They unfortunately also introduce numerous social problems, among which traffic accidents are most notoriously threatening automobile drivers and other road users. Advanced driver-assistance systems (ADAS) are under rapid development in recent years, which can necessarily reduce or even eliminate the driver errors, significantly relieving on drivers suffering or stress. These state-of-the-art ADAS mainly rely on built-in cameras, radars and ultrasound sensors to provide road sensing services for object detection, which are further advanced by recent explosion of vision and neural network technologies.

Currently, the real-time road sensing services are provided by the vehicle's built-in manufacturer software, which is usually embedded on a chip, e.g., MobilEye's EyeQ3, to provide extremely low latency, while the used models/algorithms are usually offline trained in data centers by car manufacturers as well as OEMs, making it difficult to upgrade the existing on-vehicle ADAS software and also not able to be dynamically tuned for particular local scenarios. For example, it is reported that a recent serious accident caused by Tesla Model S is because the user put his hands off the wheel for long periods and solely depended on the Autopilot Systems to drive, which turned out to be not adaptable enough for certain specific situations that caused the accident[1].

Therefore, timely training, upgrading and executing the models/algorithms for various specific local driving scenarios are essential and important towards improving the quality of the road sensing services and thus the driving safety, calling for a new and more efficient design beyond the traditional approach using standalone devices together with static models/algorithms offline trained in the datacenter/cloud. In fact, even nowadays it becomes possible for the datacenter/cloud to dynamically update the models/algorithms in ADAS, the ultra-low inference latency requirement of the real-time road sensing services (usually less than 10 ms) can still be hardly met, since it can be quite difficult for todays wide area networks to sustain a latency under 100 ms, even with the ultra high-speed link and the distributed datacenters.

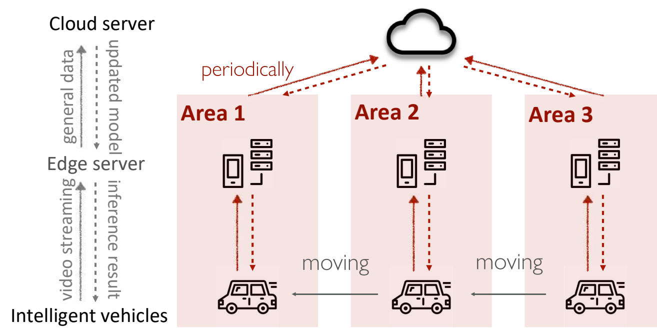

Fig. 1: The Edge Computing Framework for Intelligent Road Sensing Services

To cope with the huge network traffic and high computational demands, as well as to improve the system response time and dynamically tune the trained models, we proposed to apply the concept of *edge computing* [1] [2] to the domain of intelligent road sensing services, seeking to overcome the limitations in standalone and datacenter/cloud-based road sensing approaches. In particular, we propose an edge computing framework for intelligent road sensing services in ADAS (as shown in Fig. 1), taking the first step to add edge servers between cloud and the intelligent vehicles and moving the training models to edge servers for faster computing and updating. The wide deployment of 5G network can bring many benefits, such as low inference latency, online updating models and maintenance. Its extending services on the edge servers can tune the general road sensing model with its own specific local data circumstances, which can be leveraged to crowdsourcing collection of driving information.

However, one challenge is that the dataset for specific local cases is often not large enough, causing that the dataset may not contain enough diverse information, e.g., locations, occlusions, deformations and special weather conditions. To address this issue, we further propose to use Generative Adversarial Networks (GAN) [3] for object recognition, which can generate hard examples for an object detector to classify

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[1]Man killed in Tesla Autopilot crash got numerous warnings: https://www.cnbc.com/2017/06/20/man-killed-in-tesla-autopilot-crash-got-numerous-warnings-report.html

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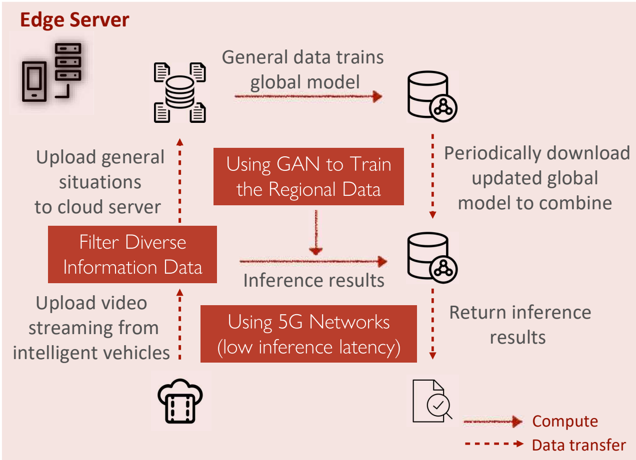
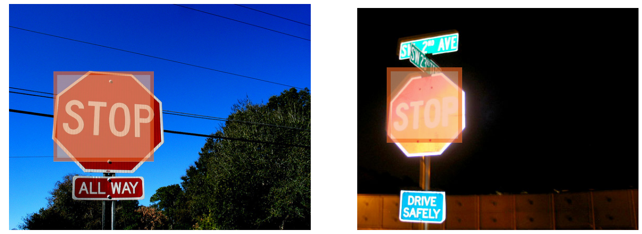


Fig. 2: Edge Computing Workflow



(a) **The Fast-RCNN model can detect road signs under good illumination condition**

(b) **The stop sign recognition with reflection using the discriminator with GAN on the edge computing**

Fig. 3: The examples of traffic sign recognition illustrate the enhancement of road sensing on the edge in special conditions

without increasing the cost for collecting large-scale training data under various specific local conditions. To illustrate the effectiveness of our solution, we have implemented an edge computing reflection case of the GAN framework app and examined its performance under various road circumstances. The experimental results demonstrate its superiority in different illumination situations.

II. System Design

Our edge computing framework for intelligent road sensing services is shown in Fig 1, which contains three main parts: cloud server, edge servers and intelligent vehicles. The most important bridge is the edge servers which closely connect to the intelligent vehicles and periodically update the global model from the cloud server. As shown in Fig 2, the edge servers provide the real-time visual inference processing. The processes run online and collect the crowdsourced driving information from the front cameras on vehicles, which is further utilized to tune the deep learning model. The backend module on the edge server accepts and stores the video streaming from the vehicle front cameras as the training data in a database, and executes our algorithms to fine tune the models. With the edge learning paradigm, each edge servers can report the extracted features in the special conditions to scale up the datasets on cloud server for future model training.

Recalling the challenge we discussed, the performance of most deep learning technologies highly depend on large-scale training data. The training datasets collected from one regional area may not be enough, and the edge server needs to spend a long time to collect enough data to improve the performance of the model. We thus propose a GAN to improve the performance of the road sensing model running on the edge. Instead of collecting all the possible situations, GAN generate examples that will be challenging for the model to classify, so that the road sensing model can become more robust to different specific local conditions.

III. Case Study and Preliminary Results

We have implemented the edge computing framework according to the workflow shown in Fig. 2. We choose the road sign's reflection situation as our case study, which is initialized with pre-training from road sign image samples. The GAN for creating reflections needs to be pre-trained before being used to improve the discriminator. As the discriminator now has a sense of the objects in the dataset, we train the GAN model by fixing all the layers in the discriminator. To initialize the GAN, given a position of the light source, we stimulate a reflection on a iron-made plane area to get a mask and apply this mask at a random position on the road sign images, where the key idea is that the GAN should learn to generate the masks which can give the discriminator high losses. With the pre-trained GAN and Fast-RCNN model, we then jointly optimize these two networks in each training iteration.

We have examined the performance of recognizing road signs running on the edge under different illumination conditions, comparing the standard Fast-RCNN [4] and our GAN based edge computing framework. The results showed that the Fast-RCNN general model can only detect road signs under good illumination condition but fail under reflection condition, as illustrated in Fig. 3(a). As for the GAN based edge computing framework, the discriminator can recognize the stop sign in Fig. 3(b) and locate it, which illustrates that our GAN based edge computing framework can improve the performance of the road sign discriminator for intelligent road sensing services in different areas.

References

[1] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile edge computing-a key technology towards 5g," *ETSI white paper*, vol. 11, no. 11, pp. 1–16, 2015.

[2] X. Ma, S. Zhang, W. Li, P. Zhang, C. Lin, and X. Shen, "Cost-efficient workload scheduling in cloud assisted mobile edge computing," in *Proceedings of IEEE/ACM IWQoS 2017*.

[3] X. Wang, A. Shrivastava, and A. Gupta, "A-fast-rcnn: Hard positive generation via adversary for object detection," in *Proceedings of IEEE CVPR 2017*.

[4] F. Yang, W. Choi, and Y. Lin, "Exploit all the layers: Fast and accurate cnn object detector with scale dependent pooling and cascaded rejection classifiers," in *Proceedings of IEEE CVPR 2016*.