Digital Twins based Blockchain Model for Space-Air-Ground Integrated Networks (SAGINs)

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Abstract:

The wide use of unmanned aerial vehicles provides a promising paradigm for improving air-ground services and applications (e.g., urban sensing, disaster relief) in air-ground integrated networks (AGINs). Digital twin (DT), which is an emerging technology that utilizes data, models, and intelligent algorithms to integrate cyber physical networks and digital virtual models, provides a real-time and dynamic simulation platform for strategy optimization and decision making in AGINs. Due to the openness and massive connectivity of AGINs, the security and reliability services in this system become an important issue. In this article, we investigate the DT envisioned secure federated aerial learning for AGINs via an aerial blockchain approach. Specifically, we propose a layered framework of DT envisioned AGINs, which comprises the construction segment, communication segment, aggregation segment, analysis segment, and operation segment. Based on this framework, we offer the applications of the proposed DT envisioned AGINs. To guarantee the security of data transmission in AGINs, we investigate the aerial blockchain-based approach for ensuring data security. Furthermore, we provide a case study of DT envisioned secure federated aerial computing in AGINs to validate the effectiveness of the proposed approach through designing the aerial blockchain and training model.

Space-air-ground integrated network (SAGIN) is envisioned as a promising solution to provide cost-effective, large-scale, and flexible wireless coverage and communication services. Since real-world deployment for testing of SAGIN is difficult and prohibitive, an efficient SAGIN simulation platform is requisite. In this article, we present our developed SAGIN simulation platform which supports various mobility traces and protocols of space, aerial, and terrestrial networks. Centralized and decentralized controllers are implemented to optimize the network functions such as access control and resource orchestration. In addition, various interfaces extend the functionality of the platform to facilitate user-defined mobility traces and control algorithms. We also present a case study where highly mobile vehicular users dynamically choose different radio access networks according to their quality of service (QoS) requirements. We justify an online service provisioning (OSP) framework to provision virtualized and micro service (VMS) to users, which can achieve efficient, flexible, and scalable service provisioning. Compared to the onboard service provisioning framework, the system bottleneck shifts from the onboard computation limitation to the network capability and robustness in OSP, which the space-air-ground integrated network (SAGIN) can ably support. First, the motivations of OSP and VMS per the current mobile application industry are identified. Then we investigate the capabilities of the SAGIN to enable the OSP framework, where the evolution of the terrestrial network, on-demand deployment of an aerial network, and global coverage with a satellite network are reviewed. Afterward, we elaborate on three major techniques of VMS provisioning in the OSP framework: application decomposition, control protocol design, and microservice placement/replacement. Finally, we design and implement a case study to demonstrate the efficacy of provisioning VMS in OSP.

The purpose is to solve the security problems of the Cooperative Intelligent Transportation System (CITS) Digital Twins (DTs) in the Deep Learning (DL) environment. The DL algorithm is improved; the Convolutional Neural Network (CNN) is combined with Support Vector Regression (SVR); the DTs technology is introduced. Eventually, a CITS DTs model is constructed based on CNN-SVR, whose security performance and effect are analyzed through simulation experiments. Compared with other algorithms, the security prediction accuracy of the proposed algorithm reaches 90.43%. Besides, the proposed algorithm outperforms other algorithms regarding Precision, Recall, and F1. The data transmission performances of the proposed algorithm and other algorithms are compared. The proposed algorithm can ensure that emergency messages can be responded to in time, with a delay of less than 1.8s. Meanwhile, it can better adapt to the road environment, maintain high data transmission speed, and provide reasonable path planning for vehicles so that vehicles can reach their destinations faster. The impacts of different factors on the transportation network are analyzed further. Results suggest that under path guidance, as the Market Penetration Rate (MPR), Following Rate (FR), and Congestion Level (CL) increase, the guidance strategy’s effects become more apparent. When MPR ranges between 40% ~ 80% and the congestion is level III, the ATT decreases the fastest, and the improvement effect of the guidance strategy is more apparent. The proposed DL algorithm model can lower the data transmission delay of the system, increase the prediction accuracy, and reasonably changes the paths to suppress the sprawl of traffic congestions, providing an experimental reference for developing and improving urban transportation.

In the intelligent transportation system, the geometry for the street is an important factor in vehicle monitoring. It helps to point out areas of interest, reduce computing costs, increased accuracy in detecting and identifying objects and facilitate data collection. In this paper, a new robust method of extracting the geometric model of the road is presented. The method is based on vehicle motion data to show the exact shape of the street without depending on the edge elements. First, the special features of consecutive frames are extracted and matched together. Second, by stretching the lines from matching these respective key points, intersections are indicated. The vanishing point is achieved by calculating the center of these intersections. Third, combining the infinity and the extremes of the motion data to tangent to the boundary of the geometry. Finally, by charting the area with the greatest matching ratio between the key points in the adjacent frame we reach the area of interest. Vietnam traffic dataset is used to verify the effectiveness and accuracy of the proposed method. Experimental results show that the proposed method has shown the correct geometry of the path. The use of motion data is a sustainable method of extracting Vanishing Point without being affected by other side effects.

The object tracking in video surveillance for intelligent traffic handling in smart cities requires an enormous amount of data called big data to be transmitted over the network using the Internet of Things. Manual monitoring and surveillance are impossible because traditional computer vision technologies are no more useful for massive processing and intelligent decision making. In this paper, a framework is proposed which enables both on spot data processing and intelligent decision making by using cloud computing. The developed application is a trained on Artificial Neural Network, which can handle different traffic techniques with congested traffic scenario and priorities traffic such as ambulance handling. The Message Queue Telemetry Transport protocol is used for green transmission with mobile access to traffic data. The results analyzed with thirty videos processed data which handle real-time data prioritization for the people for smart surveillance to fastest route and enhance the intelligent data transmission.

The advancements in Edge computing have paved the way for deep learning in real-time systems. One of the beneficiaries is an adaptive traffic control system that responds to real-time traffic observations by governing the signal phase and timings. Reinforcement Learning (RL) is extensively utilized in the literature in order to decrease traffic congestion in a road network. However, most of the previous works leverage centralized and cloud-based RL due to the computational complexity of underlying deep neural networks (DNN). Therefore, a persistent challenge towards adopting Edge learning is in devising a multi-Agent RL in which agents are simplified, and their state spaces are localized but they perform comparable to the centralized RL. This article presents a Collaborative and Adaptive Signaling on the Edge (CASE), a novel multi-Agent RL approach to control the traffic signals' phase and timing. Each signalized intersection in the road network is provided with an Edge Learning Platform which hosts an RL-Agent that observes local traffic states and learns an optimum signal policy. Moreover, CASE allows collaboration among RL-Agents by sharing their signal phase and timings to achieve convergence and performance. This collaboration is limited to one's direct neighbors only to minimize the computational complexity. We performed rigorous evaluations in terms of the choice of RL methods and their state space/reward and found that our collaborative state-space has resulted in a performance comparable to a centralized RL yet with a cost similar to the decentralized RL. Finally, a performance comparison of the CASE controller ported to the state-of-the-art Edge learning platforms is presented in this article. The results show that the proposed CASE controller can achieve real-time performance when ported to a general-purpose GPU-based platform. This arrangement achieves more than 8 times improvement in computational time over conventional embedded platforms.

SECTION I. Introduction

With the increasing number of vehicles on roads, traffic congestion is becoming a critical issue for big cities. The congestion increases travel time, fuel consumption and air pollution. Due to congestion in large cities of North America, people travelled extra 6.8 billion hours annually and consumed 3.1 billion gallons of fuel, which raised the congestion cost to ($153 billion and emission of greenhouse gases caused global warming and health risks. Moreover, frequent waiting in traffic queues may lead to "Road rage", an umbrella term used to describe a host of psychological disorders.

Countries spend billions of dollars on road expansions to avoid traffic congestion. According to the INRIX traffic scorecard report of 2017, the UK has spent £500 million, Dallas has paid $1-billion, and Germany has invested 21 million Euros in road infrastructure. However, the development of road infrastructure is not sufficient alone, in our opinion. Instead, recent developments in remote sensing and Information and Communication technologies can be leveraged to address the traffic congestion problem.

The solutions provided by intelligent transportation systems to alleviate traffic congestion fall into two categories. We can reroute the vehicles away from busy road segments and intersection as adopted in computer networks. However, vehicles in most parts of the world lack equipment to receive such directions. Alternatively, adaptive traffic signaling can be employed based on the congestion statistics or real-time monitoring on the roads. Optimizing the Signal Phase and Timing (SPaT) in an efficient, intelligent, and adaptive way can be more cost-effective to handle traffic congestion at signalized intersections. Conventional SPaT schemes deliver a fixed timing of signal phases at an intersection based on historical traffic data records. Phase timing is embedded in the Onboard Equipment (OBE) of a traffic signal or in the Roadside Equipment (RSE) of the signalized intersection and can be periodically updated. An improvement over this simplistic system is a responsive control system that uses stored configurations of SPaT to adapt the signal timings based on real-time traffic environment. Split, Cycle and Offset Optimization Technique (SCOOT) is deployed in Britain as a traffic control system that records traffic queues on the intersections. It continuously adjusts signal timings such that the sum of the queues is minimized in a specific area, based on a heuristic optimization algorithm that emits adaptive SPaT plans by using TRANSYT, an evolutionary model using platoon-dispersion equations. Alternatively, Sydney Coordinated Adaptive Traffic System (SCATS) developed in Australia does not require such models. Instead, it is a decentralized system that utilizes local controllers for traffic control. A library of preset plans is provided to minimize vehicle stop times with light demand, minimize delay with normal demand, and maximize throughput with heavy demand. Local adjustments at the top of presets are allowed to adapt to the instantaneous traffic profiles. Other widely used responsive traffic control systems include RODYN and CRONOS developed in France, UTOPIA developed in Italy, and OPAC and RHODES developed in USA.

Because SPaT can be modeled as a Markov Decision Process (MDP), dynamic programming is applied to traffic control systems in many recent studies. These dynamic programming-based schemes require a mathematical traffic model which is based on the vehicles' parameters acquired from In-Vehicle sensors. However, traditional vehicles generally lack such sensors, advocating a model-free control technique such as Reinforcement Learning (RL). At the core of RL is an Agent that learns an optimum policy iteratively by choosing an action based on the observation of its state space such that a Reward is maximized. In SPaT control, the reward may be traffic throughput at an intersection, wait time, or another figure of merit. Therefore, many recent attempts are made to solve the question of optimal SPaT pattern with deep Q-learning and Policy Gradient methods. The Deep Q-Network (DQN) is a commonly used deep Q-learning method. Whereas, one recent example of the Policy Gradient method is Proximal Policy Optimization (PPO) that solves the Partially defined Markov Decision Processes where the state is not fully defined and/or observable and where the state observations are noisy, such as the traffic signaling problem.

Despite the advantages mentioned above, the application of RL methods is often limited in real-life systems due to the computational complexities of underlying Deep Neural Networks (DNN). The compute kernels of DNNs are computationally intensive; therefore, centralized and cloud computing resources equipped with deep learning accelerators (DLA) are often leveraged. In traffic control, however, a centralized cloud-based solution is deemed sub-optimal due to communication bandwidth and real-time latency requirements. Alternatively, Fog and Edge computing have been proposed to alleviate these bottlenecks, especially in the context of real-time applications.

This research focuses on the use of Embedded Deep Learning at the Edge of traffic control networks to alleviate the above-mentioned problems related to bandwidth and latency. Because, the embedded platforms (with DLAs) are often resource-constrained to smaller DNNs, we argue that the RL must be simplified and truncated, for example, to the Signal control at a single road intersection, resulting in a decentralized multi-Agent RL. However, previous studies in this domain show that the decentralized multi-Agent RL may not converge well, especially in the traffic control problem, because an optimal signal control at one intersection depends on the signal state at other intersections. In order to converge, these individual RL Agents must not work in silos. Instead, they should collaborate to maximize a joint reward by sharing their decisions. Thus, there is a need to propose a decentralized and collaborative, multi-agent, Reinforcement Learning-based solution which can leverage contemporary edge learning platform to infer optimal signal phase and timing in a real-time traffic control system. To address this problem, we propose a Collaborative and Adaptive Signaling on the Edge (CASE) which is an efficient and scalable multi-Agent RL-based traffic control system. *To the best of our knowledge, CASE is the first attempt to deploy deep learning on Edge of a responsive and adaptive traffic control network.*

We addressed the following research challenges to employ a multi-Agent RL in real-time traffic control systems.

- Defining of an optimal state-space, e.g., consisting of vehicle queue length, traffic throughput, etc., that impact the RL performance.
- Choice of a suitable Reward function, e.g., average throughput or average waiting time experienced by the vehicles.
- Scale of Horizon: Ideally, a truly optimal SPaT pattern should consider all the intersections of a road network. Alternatively, considering only local state-space at a road intersection is faster to process but may not converge well. A balanced horizon is required that includes a subset of nodes that effectively reflect the system state.

Our CASE system is backed by a rigorous evaluation based on FLOW, an RL framework that uses the SUMO traffic simulator as an environment in which each signalized intersection is modeled as an RL Agent. We compared the results for a Fixed Time, a conventional adaptive system (SCOOT), and our DQN-based D-CASE and PPO-based P-CASE setups. In performance evaluations, the CASE system was deployed on an Edge Learning Platform as a part of Roadside equipment to infer the SPaT pattern for concerning intersection by using a collaborative state-space, including local traffic observations (from traffic cameras) and SPaT information from neighboring intersections. When CASE is ported to general-purpose GPU-based platforms, it achieved more than 8 times improvement in computational time for Nvidia's Jetson Nano Development Kit over Raspberry Pi4 based conventional embedded platform. Reducing the horizon only to the neighboring intersections has allowed real-time communication to be affordable for SPaT sharing in a Multi-agent RL. Contrary to previously proposed and adopted solutions, the CASE system focused on the average wait time of vehicles as RL reward, and thus reducing the congestion in a psychological sense and mitigating the "Road rage".

The rest of this article is organized as follows. The next section presents the background, recent advancements, and motivation behind this work. Section III presents the CASE as our proposed edge-based deep RL system, highlights the methodology of our work, and introduces the RL algorithms we used for decentralized and collaborative traffic control. The experimentation and the results are presented in Section IV. Section V presents deductions based upon discussions on the results. Finally, Section V1 concludes the article and highlights our future work.

SECTION II. Background and Related Work

At a traffic intersection, multiple traffic lights work in synchronization to manage the flow of traffic, where each traffic light switches among the signals of Red (R), Yellow (Y) and Green (G). The time duration of staying at a particular signal out of Red, Yellow, or Green is termed as one phase of the traffic light. Conventionally, the green-light phase and red-light phase are managed for every traffic inflow arm, whereas the yellow-light phase is set as a transition time to handle between green and red signals. The number of possible traffic lights at a traffic intersection depends on its inflow roads, which also decides the total number of phases at the junction. A crossroad junction is shown where three traffic lanes on each road segment have traffic control signals. The traffic light controller is used to manage the vehicle flow by changing the phases of traffic lights. The phases of traffic lights are changed in a cyclic fashion that keeps on repeating with a predefined or dynamically adjusted signal phase duration, also known as phase split. The traffic lights at an intersection need to change in such combinations that avoid conflict of traffic flow in multiple directions.

Show All

Approaches being used in the literature for signal planning to avoid traffic congestion are categorized in this section with respect to the control algorithm as well as the overall traffic system organization and architecture. The first group consists of the traditional static approaches having fixed phase time and sequence. The second group utilizes the adaptive approaches for traffic signal control and tries to find a globally optimal solution by monitoring the traffic situation. The third group is constituted of machine learning/deep learning-based approaches that provide dynamic phase changes.

A. Traditional Approaches

A SPaT optimization depends on the data from sensors to observe the vehicles passing through the road intersections. Loop sensor-based detectors are traditionally used for vehicle detection; however, such sensors can only detect passing by vehicles. More recently, the use of cameras is becoming a new source of data to get more sophisticated vehicles related to data. With advances in the image processing techniques and availability of high computation speed, Video data from the camera can be processed in real-time to extract a detailed representation of the traffic situation on roads. Traditional SPaT techniques usually suppose that every intersection is independent of other intersections in a region and try to optimize the signal timings of every intersection independently. Such techniques develop a traffic model and use them to calculate the cycle length of signals of an intersection. Webster is one such technique that assumes that the traffic flow at an intersection is uniform for a certain duration. Based on this assumption, this technique calculates the intersection's cycle duration and decides the phase split to minimize the travel time of all the vehicles at an intersection. GreenWave is another traditional signaling technique that tries to reduce the number of stops for vehicles traveling in a certain direction. This is achieved by implementing the same cycle length at all the intersection. This method helps to reduce the stopping time of vehicles moving in a certain direction by providing them a green wave. This minimizes their number of stops and optimizes the unidirectional traffic, using offsets in SPaT. Another traditional approach, Maxband provides a mechanism to reduce the number of stops for vehicles traveling in two opposite directions. This technique also implements the same cycle length on all the intersections.

B. Actuated and Adaptive Approaches

Actuated control decides a signaling plan based on the requests for a green signal from the current and other completing phases. Based on the distance of oncoming vehicles from a signal and the number of waiting vehicles, this technique decides whether the duration of green signals should be extended or not. A similar approach, Self-Organizing Traffic Light Control (SOTL) decides the extension in the current green phase on the basis of the number of vehicles approaching an intersection. Max pressure control balances the queue length between neighboring intersections by minimizing the pressure of the phases of an intersection, where the pressure is defined as the difference between the overall queue length on incoming approaches and outgoing approaches. Sydney Coordinated Adaptive Traffic System (SCATS) works on the principle of taking predefined signal plans as input and iteratively selects from these plans. SCOOT records traffic queues on the intersections and continuously adjusts signal timings such that the sum of the queues is minimized in a specific area.

A dynamic speed-truncated normal distribution model and dynamic Robertson model with dynamics that outperforms the existing methods. In recent developments, vehicle infrastructure integration (VII) technology collects state space information about upcoming vehicles in terms of their location and speed, which is then used to manage the timing of a traffic signal. The system works for individual intersections with less state-space parameters that can be enhanced and shared with nearby intersections to manage the traffic flow in a collaborative manner. The technology of connected automated vehicles to obtain vehicles ‘identification, position, speed, and acceleration in addition to traditional traffic data, and applied dynamic programming and most predictive model approach to reduce the traffic congestion. However, dynamic programming requires a model that is not readily available in traditional traffic scenarios and depends on parameters that explicitly require Vehicle to Intersection Communication, which legacy vehicles generally lack.

C. Intelligent Approaches

Model-Free Reinforcement Learning is an answer to optimization problems of those Markov Decision Processes for which state space is not fully observable, or a mathematical model is not well-developed or well-understood. A good survey on the application of RL methods to the adaptive traffic control systems is discussed that DNNs could be used to learn the dynamics of a traffic system and defined a signal plan by modeling the control action and system state. It could be efficient if the problem is mapped to reinforcement learning. A Q-learning based technique was also used in to optimize the traffic signals, but each signal optimized itself without looking at the other signals’ policy. A multi-agent approach was used in to avoid congestion, but the state parameters were not enough to attain a global optimum. The communication between the agents was another overhead. Similarly, two decentralized actor-critic algorithms used where in the actor step, an agent takes action without affecting the policy of other agents. In the critic step, the agent shears its value function to its near agents, which is used in the successive actor step. But the recursive process has computation overhead. Mini-max multi-agent deep deterministic policy gradient for reinforcement learning performs best in cooperative and competitive scenarios. A deep reinforcement learning model to control the traffic cycle by getting the position and speed of vehicles from different sensors. However, the environmental observation was not enough to decrease the overall congestion, and agents make their policy without looking at the neighboring signal’s state. However, the real environment consists of multiple intersections. So, to resolve the overall traffic congestion problem in a region, there must be a collaborative state-space that carries an environment observation with neighboring signal’s state information.

D. Organization and Architectures

In order to effectively respond to real-time traffic, close interactions between intersections are pivotal. In addition, all the interactions over the network must be synchronized. On the other hand, prior works in decentralized traffic control suffer due to partial observability of the whole transportation network as well as its high dynamic traffic patterns. A distributed control method but assumed that the sensor information within the whole area was easily obtained from centralized servers. This may suffer a communication bottleneck in a huge urban area as the coming vehicles follow a Poisson distribution to build a decentralized coordination algorithm. A centralized deep learning model forces multiple participants to pool their data in a centralized server to train a global model on the combined data. However, this centralized Cloud-based machine learning required enormous bandwidth and computer resources. To accelerate inference, proposed a distributed DNN (DDNN) architecture across the Cloud, the Fog, and the Edge devices and allowed fast inference on end-devices and complex inference on the Cloud. Fog computing with deep learning by dividing the pre-trained Cloud-level model into two parts: the lower layers near the input data are deployed into Fog nodes, and higher layers are kept into the Cloud. However, they are keen on deploying a pre-trained model to offload processing during inference while neglecting the computation-intensive training process.

Performance of Embedded Learning Platforms

We listed the details of three selected embedded systems for the choice of ELP in, highlighting their CPU, memory, GPU, and compute capabilities in terms of Giga Floating-point Operations per second. Raspberry Pi boards are popular in the Camera/Vision processing, whereas NVIDIA's Jetson Nano board is equipped with CUDA cores, specifically provided to run compute-intensive DNN kernels. Both platforms support Linux distributions specifically tailored to the board capabilities and support the Keras/TensorFlow framework, which is employed in this work as an underlying software kernel of DNNs. To compare, we executed a pre-trained version of P-CASE on these platforms and reported the average SPaT calculation time as the response time in. Due to CUDA Compute Capability, Jetson Nano board outperforms traditional embedded platforms in machine learning applications with DNNs. Therefore, this platform is recommended as ELP in the CASE controller.

Discussion

In the domain of Reinforcement Learning, DQN and PPO are representatives of action-value and policy gradient methods. In Section IV, we compared both methods in the context of the SPaT problem. We found that PPO, along with a collaborative state space, minimizes the wait time experienced by vehicles by maximizing RL reward. We then compared these RL methods with a Fixed-timed control (FT) and a representative of the conventional adaptive techniques (SCOOT). Based on the results in, we found that RL-based techniques work best in scenarios with high traffic congestion. In particular, our proposed method (P-CASE) reduces the average wait time by half as compared to the Fixed-Timed SPaT, when the congestion (marked by average queue length) is as high as 80%.

The body of the previous research efforts in intelligent traffic control is dedicated to a centralized control where a holistic state space of a regional road network is acquired to train RL's internal DNNs. We compared the P - CASE performance to a centralized Single Agent RL (with PPO and holistic Intelligent State Space S2) and a Decentralized and Isolated Multi-Agent RL (with PPO and holistic Intelligent State Space S2). We found that P-CASE achieves similar wait time reduction as compared to a centralized control with costs comparable to the decentralized control. These costs include bandwidth requirements to collect traffic statistics in real-time and to disperse SPaT messages to signal controllers at intersections. In addition, the computational complexity of centralized methods is expected to scale up when more intersections are added to the road network. Finally, the addition of a new input would require rebuilding the underlying DNNs, followed by the computation-hungry process of re-learning. Therefore, it can be deduced that centralized control is not scalable in urban traffic control problems. On the other hand, a decentralized control where each intersection controls its own SPaT, is trivially scalable. However, a multi-agent RL with agents in silos is inefficient at best and unstable at worst in traffic control because traffic incident on an intersection depends on the signal state of the neighboring intersections. Therefore, it is imperative to share the SPaT decisions among the neighboring intersections so that individual RL-Agents may converge to a global reward. This deduction is also supported by the performance of P-CASE.

Once we established the applicability of Multi-agent RL, we ported the proposed CASE controller to the contemporary Edge Learning Platforms to analyze and evaluate its real-time performance. We find that Deep Learning Acceleration offered by the Jetson Nano Development kit is key to real-time performance, which is requisite in a traffic control problem. Moreover, the reduced state-space as compared to one required in a centralized control is bandwidth-efficient. Due to the reduced size of underlaying DNNs, Nano ELP was able to complete an inference (computing SPaT based in 107ms on average. To compare Raspberry Pi3 and a newer and more resourceful Raspberry Pi4, ELPs rendered the inference time of 1560ms and 906ms, respectively. Therefore, based on our rigorous evaluations and discussions above, the proposed Collaborative and Adaptive Signaling on the Edge constitutes a real-time, intelligent, and a scalable traffic control system that greatly reduces the average wait time under congestion in urban road networks.

SECTION VI. Conclusion and Future Work

We have proposed a Collaborative and Adaptive Signaling on the Edge (CASE) which employs an Edge computer to accelerate its compute kernels for solving the SPaT problem in a region. Based on results and discussions, we conclude that our proposed decentralized and collaborative Multi-agent RL (P-CASE) is more cost-effective and efficient to reduce traffic congestion on traditional signalized intersections as compared to the conventional fixed-timed and adaptive solutions. Although evaluations are performed offline with a traffic simulator in this work, we ported RL algorithms to ELPs and found that embedded deep learning accelerator solutions, like NVIDIA Jetson Nano, greatly reduce the computations time incurred in RL algorithms. A future work will evaluate the real-time performance of the proposed CASE framework at real-life signalized intersections, to further assist the deployment of Edge-based deep learning technologies into the adaptive control of traffic systems.

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