Top Level Newsletter: Connected Vehicle

(Published by IEEE Orange County Section)

February 2021
Vol 15.0

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Systems Research Development and Innovation

Vol 15.0 (this issue): Concept of Fluid Flow for Vehicular Traffic Lanes, How to Validate Simulation Using Public Data Sets, and Object Detection Under Rainy Conditions for Autonomous Vehicles. The last two from IEEE Signal Processing - Autonomous Driving (part 2): "Learning and Cognition"

Previous issues:
Vol 14.0: 5G mmWave communications, Mobile Edge Computing, mmWave small cell networks, Software Verification and Validation, Unmanned Aerial Vehicles, and Network Slicing
Vol 13.0: Data Science/ AI/ Deep Learning/ 5G, Global Navigation Satellite System (GNSS), mmWave Vehicular Communications
Vol 12.0: 7 topics on Autonomous Vehicles Technology,1 topic on 5G Radio Access Network Slicing
Vol 11.0: Autonomous Vehicles Should Start Small, Go Slow, 5G Radio Access Network Slicing, from IEEE Signal Processing - Autonomous Driving (part 1): "Sensing and Perception "
Vol 10.0: GNSS Special Issue, Intelligent Transport Systems magazine, Fall 2020.
Vol 9.1: Data Science and AI for Communications
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Vol 7.0: COVID-19 and Connected Vehicle
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Vol 5.1: Co-operative Automated Driving
Vol 4.0: Current Sensor Technology

This newsletter is intended to provide the IEEE member with a top level briefing of the subject under review. Instead of a cumulative approach, as adopted previously, it will now only feature new content. For older content, please access previous volumes.

The objective is to provide a platform for fast learning and quick overview so that the reader may be guided to the next levels of detail and gain insight into correlations between the entries to enable growth of the technology. Intended audiences are those that desire a quick introduction to the subject and who may wish to take it further and deepen their knowledge. This includes those in industry, academia or government and the public at large. Descriptions will include a range of flavors from technical detail to broad industry and administrative issues. A (soft) limit of 200 to 300 words is usually set for each topic, but not rigorously exercised. As descriptions are not exhaustive, hyperlinks are occasionally provided to give the reader a first means of delving into the next level of detail. However, it is not the intent to make this a forest of hyperlinks. The reader is encouraged to develop a first level understanding of the topic in view. The emphasis is on brief, clear and contained text. There will be no diagrams in order to keep the publication concise. Related topics in the case of Connected Vehicle technology, such as 5G cellular and the Internet of Things will be included. The terms Connected Vehicle and Automated Driving will be used inter-changeably. The publication will be updated periodically. Articles from other published sources than IEEE that add to the information value will occasionally be included.

This newsletter forms part of the regional Advanced Technology Initiative (ATI) of which connected vehicles form a constituent part. Technical articles solely from IEEE journals/magazines are referred to by their Digital Object Identifier (DOI) or corresponding https link. The link for each article is provided. Those readers who wish to delve further to the complete paper and have access to IEEE Explore (www.ieeexplore.ieee.org) may download complete articles of interest. Those who subscribe to the relevant IEEE society and receive the journal may already have physical or electronic copies. In case of difficulty please contact the editor at kaydas@mac.com. The objective is to provide *top level guidance* on the subject of interest. As this is a collection of summaries of already published articles and serves to further widen audiences for the benefit of each publication, no copyright issues are foreseen.

Readers are encouraged to develop their own onward sources of information, discover and draw inferences, join the dots, and further develop the technology. Entries in the newsletter are normally either editorials or summaries or abstracts of articles. Where a deepening of knowledge is desired, reading the full article is recommended.

1. Lane-Free Artificial-Fluid Concept for Vehicular Traffic, Markos Papageorgiou et al

Proceedings of the IEEE (Volume: 109, Issue: 2, Feb. 2021), pp 114 - 121

Abstract: A novel paradigm for vehicular traffic in the era of connected and automated vehicles (CAVs) is proposed, which includes two combined principles: lane-free traffic and vehicle nudging; the latter implying that vehicles may be "pushing" (from a distance, using communication or sensors) other vehicles in front of them. This traffic paradigm features several advantages, including smoother and safer driving; increase of roadway capacity; and no need for the anisotropy restriction. Anisotropy is the property of a material which allows it to change or assume different properties in different directions as opposed to isotropy. It can be defined as a difference, when measured along different axes, in a material's physical or mechanical properties. The proposed concept provides the possibility to actively design (rather than model or describe) the traffic flow characteristics in an optimal way, i.e. *to engineer the future CAV traffic flow as an efficient artificial fluid*. Options, features, related prior work, application domains and required research topics are discussed. Preliminary simulation results illustrate some basic features of the concept**.**

Introduction: Vehicular traffic has evolved as a crucial means for the transport of persons and goods, and its importance for the economic and social life of modern society cannot be overemphasized. On the other hand, recurrent vehicular traffic congestion, which appears on a daily basis, particularly in metropolitan areas has been a serious problem that calls for drastic solutions. Traffic congestion causes excessive travel delays, substantial fuel consumption and environmental pollution, and reduced traffic safety. Conventional traffic management measures are valuable but not sufficient to address the heavily congested traffic conditions, which must be addressed in a more comprehensive way that exploits gradually emerging and future ground-breaking capabilities of vehicles and the infrastructure.

Vehicle automation has been a research topic in the past several decades, and the concept of automated highway system (AHS), envisioned in the 1990s, triggered a plethora of related results with lasting value. During the last decade, efforts have strongly intensified, notably by the automobile industry and by numerous research institutions, to

develop and deploy a variety of vehicle automation and communication systems (VACSs) that are revolutionizing the capabilities of individual vehicles.
VACSs may be distinguished in vehicle automation systems ranging from relatively weak driver support to highly or fully automated driving, and vehicle communication systems enabling vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. Some low-automation VACSs, such as adaptive cruise control (ACC), are already available in the market.
ACC automatically controls the vehicle speed according to the desired speed selected by the driver, or adjusts the distance in the case of a slower front vehicle. Moreover, numerous companies and research institutions have been developing and testing in real traffic conditions highly automated or virtually driverless autonomous vehicles that monitor their environment and make sensible decisions, not only about car-following, but also about lane changing. There is a variety of methodologies employed for their movement strategies, ranging from artificial intelligence (AI) techniques to optimal control methods. It should be noted that the relatively high-risk task of lane changing is particularly challenging, both methodologically and practically.
This article proposes a novel paradigm for vehicular traffic, applicable at high levels of vehicle automation and communication and high penetration rates. Specifically, we assume that vehicles communicate with each other (V2V) and with the infrastructure (V2I) at sufficient frequency, distance, and bandwidth, and drive automatically, based on their own sensors, communications, and an appropriate movement control strategy. Vehicles may be of various types (e.g., electric or with internal combustion engine) and sizes (cars, vans, buses, trucks, motorcycles) and may have a range of desired (or allowed or achievable) maximum speeds and acceleration capabilities. The proposed concept, called henceforth TrafficFluid is based on the following two combined principles.
1. Lane-free traffic: Vehicles are not bound to fixed traffic lanes, as in conventional traffic, but may drive anywhere on the 2-D surface of the road, respecting the road boundaries.
2. Nudging: Vehicles communicate their presence to other vehicles in front of them (or are sensed by them), and this may exert a "nudging" effect on the vehicles in front. For example, vehicles in front may experience (apply) a pushing force in the direction of the line connecting the centers of the nudging vehicle and the nudged vehicle in front.
(706 words).
DOI: https://doi.org/10.1109/JPROC.2020.3042681

2. Simulating the Autonomous Future: A Look at Virtual Vehicle Environments and How to Validate Simulation Using Public Data Sets, Dean Deter et al
(IEEE Signal Processing Magazine, Vol 38, Issue 1, January 2021), pp 111 – 121
Abstract:
The rapid evolution of autonomous vehicles (AVs) has exposed the need for fast-paced development and testing processes of a variety of perception, planning, and control algorithms. To expedite development, the AV industry and researchers leverage virtual vehicle environments to simulate a range of test scenarios that may otherwise be costly or difficult to conduct on a real test track. However, the various virtual environments may have different results depending on the fidelity of various simulation features, such as vehicle dynamics, sensor simulation, and environment recreation. This tutorial article examines a proposed framework for constructing, parameterizing, and validating a virtual vehicle environment using an existing AV data set. First, an overview of several open source and commercially available simulation tools, including their associated workflows, for scene and scenario creation is presented. Next, various

open AV data sets are examined to inform the data set selection for the validation framework. Then, an example workflow of recreating a real-world scene from the selected data set in a simulation tool with various emulated sensors parameterized to match the data set is demonstrated. Finally, an example AV-perception algorithm is subjected to data streams from virtual and real-world environments and suggested metrics for analyzing the results are discussed.

Introduction

One of the primary focus areas for advancing the capability of AVs is to develop, train, and test AV algorithms using imagery and sensor data under a variety of environmental and driving conditions. A main challenge of this focus area is the sheer volume of testing and validation needed to complete many of the edge cases presented by AV operation. As a start, millions of miles have been driven by AVs, and a large amount of data has been collected on test tracks, closed roads, and public roads by various AV entities. For example, real-world data sets, such as the KITTI Vision Benchmark Suite, the Berkeley Deep Drive (BDD), the Lyft Level 5 AV data set, the Waymo Open Dataset], and the nuScenes data set have been collected by vehicles instrumented with a variety of sensors, such as cameras, lidars, radars, Global Navigation Satellite System (GLONASS), and inertial measurement units (IMUs). These data sets have been used for benchmarking and as a toolset for training and testing AV algorithms. Yet, researchers realize that there are still many arbitrary and/or dangerous situations that cannot be covered by the current extensive testing and data collection efforts. Some data sets, including the INTERACTION data set, have tried to address these situations but still lack vehicle data such as real latitude, longitude, raw image data, or vehicle sensor streams typically used for testing and validation.

To address these challenges, researchers have developed open source virtual environments using game engines such as Unreal Engine and Unity. These virtual environments, such as CARLA, LGSVL Simulator, SYNTHIA, and Virtual KITTI, aim to provide a flexible platform for developing and testing AV algorithms under a variety of possible traffic, lighting, weather, and other environmental and driving conditions. Although these virtual environments can be photorealistic, they are primarily used to generate scenarios for on-road edge cases, computer vision development, and machine learning (ML) applications; none of them have yet emulated a full suite of high-fidelity or physics-based AV sensors (e.g., cameras, lidars, and radars).

In addition to open source environments, several companies including AVSimulation, Cognata, dSPACE, ESI, IPG Automotive, Metamoto, MSC Software, and Siemens offer commercial toolchains for the development and validation of customers' AV algorithms. In contrast to most open source toolchains, many of these environments offer full sensor support and characterization as well as a high level of scenario customization. Furthermore, these tools often contain support for hardware-in-the-loop (HIL) (e.g., controller-in-the-loop, camera-in-the-loop, and sensor-in-the-loop), have full development suites, and can have high levels of simulation photorealism. Established ties to other commercial tools are also common, including software packages such as Aimsun, MATLAB/Simulink, GT-Suite, rFpro, SUMO, and VISSIM, which can help streamline workflow and cut development time for researchers, computer scientists, and engineers. A selection of both open source and commercial toolchains are covered in this article, as both solutions work to archive answers and results to varying research goals and challenges for AV testing and development as well as academic pursuits. References to all the named tools mentioned are available in the text.

All of these tools have highlighted a significant need for R&D into the ability to generate synthetic sensor data streams (in addition to synthetic imagery) from virtual environments injected into AV controllers or a full AV on a dynamometer. The AV research community has begun to investigate whether artificial intelligence (AI) drivers and ML perception algorithms can be trained on purely synthetic data, a combination of synthetic and recorded data, or if only real-world data are acceptable. Furthermore, whether AI algorithms developed to drive the vehicle in a virtual environment translate to controlling the vehicle in the real world where dynamics and perception are noticeably different must also be determined.

To answer these questions and bridge the gap between virtual environments and existing real-world data sets, there is a need to develop a framework that not only creates a “digital twin” of the real-world environment but also emulates the data streams of a full suite of sensors that are commonplace on AVs to increase fidelity and accuracy. This would enable realistic autonomous driving simulations in virtual environments. Moreover, it is important to evaluate how similarly or differently various perception and control algorithms respond to synthetic data injection versus data feeds from real-world sensors. All of these improvements depend on the ability of the aforementioned tools to continuously improve and serve as the centerpiece of AV testing and development. (734 words)

Sub-titles: Introduction (as above) / Current State of Selected Simulators/ Current State of Data Sets/ Evaluation Metrics/ General Workflow for Synthetic Environment Creation and Validation/ Example Workflow and Use Case/ Conclusions

DOI: https://doi.org/10.1109/MSP.2020.2984428

3. Object Detection Under Rainy Conditions for Autonomous Vehicles, Mazin Hnewa et al (IEEE Signal Processing Magazine, Vol 38, Issue 1, January 2021) pp 57-63

Abstract: Advanced automotive active safety systems, in general, and autonomous vehicles, in particular, rely heavily on visual data to classify and localize objects, such as pedestrians, traffic signs and lights, and nearby cars. However, the performance of object detection methods could degrade rather significantly in challenging weather scenarios, including rainy conditions. Despite major advancements in

the development of "deraining" approaches, the impact of rain on object detection has largely been understudied, especially in the context of autonomous driving.

Introduction: Emerging autonomous vehicles are employing cameras and deep learning- based methods for object detection and classification. These methods predict bounding boxes that surround detected objects and classify probabilities associated with each bounding box. In particular, convolutional neural network (CNN)-based approaches have shown very promising results in the detection of pedestrians, vehicles, and other objects. These neural networks are usually trained using a large amount of visual data captured in favorable clear conditions. However, the performance of such systems in challenging weather, such as rainy conditions, has not been thoroughly surveyed or studied.

Depending on the visual effect, adverse weather conditions can be classified as steady (such as fog, mist, and haze) or dynamic, which have more complex effects (such as rain and snow). In this article, we focus on rain because it is the most common dynamic challenging weather condition that impacts virtually every populated region of the globe. Furthermore, there has been a great number of recent efforts that attempt to mitigate the effect of rain in the context of visual processing. Rain consists of countless drops that have a wide range of sizes and complex shapes, and spreads randomly, with varying speeds when falling on roadways, pavement, vehicles, pedestrians, and other objects in the scene. Moreover, raindrops naturally cause intensity variations in images and video frames. In particular, every raindrop blocks some of the light that is reflected by objects in a scene. In addition, rain streaks lead to low contrast and elevated levels of whiteness in visual data. Consequently, mitigating the effect of rain on visual data is arguably one of the most challenging tasks that autonomous vehicles will have to perform, due to the fact that it is quite difficult to detect and isolate raindrops, and it is equally problematic to restore the information that is lost or occluded by rain.

Meanwhile, there has been noticeable progress in the development of advanced visual deraining algorithms. State-of-the-art deraining algorithms, however, are designed to remove the visual impairments caused by rain, while attempting to restore the original signal with minimal distortion. Hence, the primary objective of these algorithms, in general, is to preserve the visual quality as measured by popular performance metrics, such as the peak signal-to-noise-ratio and structure similarity index (SSIM). These metrics, however, do not reflect a viable measure for analyzing the performance of the system for more complex tasks, such as object detection.

Conclusions: We believe there is an overarching consistent message regarding the limitations of the surveyed techniques in handling and mitigating the impact of rain for visuals captured by moving vehicles. We recap some of our key findings and point out potential directions.

1) The lack of data, and especially annotated data, that captures the truly diverse nature of rainy conditions for moving vehicles is arguably the most critical and fundamental issue in this area. Major industry players are becoming more willing to tackle this problem and more open about addressing this issue publicly. Consequently, a few related efforts have just been announced and actually commenced by high-tech companies. These efforts are specifically dedicated to operating fleets of autonomous vehicles in challenging and diverse rainy weather conditions, explicitly for the sake of collecting data under these conditions. After years of testing and millions of driven miles conducted primarily in favorable and clear weather, there is a salient admittance and willingness to divert important resources toward data collection in challenging weather conditions that will be encountered by autonomous vehicles.

2) Despite the recent efforts to collect more diverse data, we believe that generative models could still play a crucial role in training object detection methods to be more robust and resilient in challenging conditions. Due to the fact that these frameworks do not require annotated data, their underlying generative models could be useful in many ways. First, they could fill the gap that currently exists in terms of the lack of real annotated data in different weather conditions; hence, progress in terms of training and testing new object detection methods could be achieved by using these generative models.

Second, even after a reasonable amount of annotated data captured in natural rainy conditions becomes available, the generative models could still play a pivotal role in both the basic training and coverage of diverse scenarios.

Image-to-image translation (I2IT) is a well-known computer vision framework that translates images from one domain , e.g., clear weather, to another domain (rainy conditions) while preserving the underlying and critical visual content of the input images.

Unsupervised image to image translation (UNIT) models could always generate more data that can complement real data, and this could be quite helpful to further the basic training of object detection methods. Furthermore, despite the number of various rainy condition scenarios there will always be a need for capturing certain scenarios not included in a real data set. In that context, generative models could be used to produce data representing the scenarios that are missing from the real data sets, and hence they could increase the coverage and diversity of the cases that object detection methods can handle.

3) There is a need for novel deep learning architectures and solutions that have capacity for handling object detection under diverse conditions. Designing a neural network that performs quite well in one domain yet degrades in others is not a viable strategy. In general, training the leading object detection

architectures through a diverse set of data does not necessarily improve the performance of these. There is opportunity for researchers to make key contributions. (995 words)

DOI: https://doi.org/10.1109/MSP.2020.2984801