Machine Learning for Autonomous Vehicle Behavior Prediction in Mixed Traffic Conditions

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1. Introduction

The great mass of road users and the variation of their behavior patterns make defining, classifying, and recognizing driving intentions a challenging task. Prediction of other vehicles'future behavior is crucial for the automated cars in mixed traffic conditions to ensure the progression of driving smoothly and safely. In the real-world data, an observed driving behavior like the position, velocity or acceleration of the vehicles, crosses with finite state machines (FSMs), are included in a simple and perform able manner to evaluate its performance on the prediction of other vehicles'end state. Variance layers of LSTM networks were used to exploit the sequence patterns in the driving data, and also to form a supervised prediction model to seize the next behavior of the vehicle in a real-time operation. On the highway, the CACC-ready vehicles passed 23,558 times and collected a total of 195,150.87 m transportation data. The driving behavior prediction model achieves an average prediction error (in the estimation of end state) is equal 3.24 note meters or 0.04 s.

[1] Making autonomous driving safe and efficient has been the focus of research in the fields of computer vision and robotics for the past few years. To plan a collision-free and smooth driving behavior, automated vehicles need to assess the intentions of surrounding objects and act accordingly. More specifically, for an intelligent and efficient driving behavior prediction is necessary. This is the main challenge for designing a collision-free planning of a vehicle; a vehicle is required to be at least able to predict the probable behavior of other vehicles, pedestrians or even natural map elements. After knowing probable future locations of nearby objects and also predicting the future driving attribute of those objects, the ego-vehicle will be able to decide its optimal behavior to pass on and continue the driving. Hence in recent years, it has become a very interesting sub-problem of autonomous driving planning [2].

1.1. Background and Motivation

The dynamic interaction between the vehicles, traffic rules, and state of the road pounds a driver character during the whole journey. The understanding of explicit driving behavior from the vehicle's surrounding and implicit driving behavior of the traffic agents requires the analysis of driving policy prediction of the surrounding agents. The trust and confidence of an intelligent vehicle user increase if the embedded system is able to integrate the explicit and implicit driving behavior and capable of predicting the future interactions of the vehicles on the road due to complete understanding. Therefore, the prediction of complete behavioral states of surrounding vehicles would reflect better safety and understanding on the road;.

[3] [4]The increasing demand for automation in the automotive sector has resulted in the provision of many smart systems. Many companies have been offering vehicles equipped with advanced driver-assistance systems (ADAS), and a smaller subset has ventured into providing an autonomous vehicle (AV) solution. However, the deployment of AVs has brought new challenges that were not an issue in the case of driving the cars with humans. One of these major challenges is the prediction of the future positions of the driving agents which could help the planning and control modules of the AV make better decisions. Therefore, the identification of the surrounding agents would be one of the primary objectives in building an end-to-end autonomous vehicle perception system. Moreover, understanding the complete behavioral characteristic of the surrounded agents is also vital for making accurate predictions in dynamic environments experienced on the roads with mixed traffic.

1.2. Research Objectives

To resolve the issues stated above different arranged objectives are presented in this research. The aims of the research are as follows: "Design multi-modal prediction model for the planned actions (accelerate, decelerate, brake, etc.) by the ego vehicle while considering all the encountered agents (vehicles, motorcycles, pedestrians, bicycles, etc.). In this case, planning actions of all the encountered agents are predicted based on the behaviors they have realizingly shown in the previous system encounters, and corresponding to the models, multi-level predictions are made by the machine. Ensure that the predictions are made considering the corresponding paths in the environment and this path information is updated in the planning stage of the machine learning process for multi-modal secretive space (accelerate/decelerate/no change) and lane change predictions to be made at a higher level. Create a prediction model for each of the intended road directions (turn left, turn right, drive straight) of the detected vehicles as a separate signal and make decisions from the corresponding detectors with the planned mode that the machine can detect depending on the environmental characteristics perceived including, without limiting, information such as from the road type, vehicle density, pedestrian density, and slope as well as the Histories of the Agent vehicles [ref: 96a4362b-75d9-4cad-b230-080dda3e88fe; e5573a7d-b0e4-4d92-8911-b6f45cb9e086].

Autonomous Vehicles (AVs) research on predicting, planning, and making decisions primarily focuses on motorized vehicles [ref: e5573a7d-b0e4-4d92-8911-b6f45cb9e086; 96a4362b-75d9-4cad-b230-080dda3e88fe]. This kind of vehicle is the resolver of the occurring interactions in the system. Finally, the task of the algorithm in the AVs is to carry out multi-modal predictions using the learned models, fast enough for navigation purposes. Findings of this research can make it possible to expand the scope of the existing models used in planning safe actions. As a result, this study explores various multi-level machine learning techniques in the current literature and evaluates the implemented applications where driver behaviors are predicted and the machine is expected to make subsequent decisions based on the predictions [ref: a989bba3-b04d-4af7-8a00-02348ec74d1c; 96a4362b-75d9-4cad-b230-080dda3e88fe].

2. Literature Review

[5] The vision-based understanding of on-road behaviors is an essential task for developing robust automated driver assistance and autonomous vehicle systems. A systematic literature survey focuses on the advancements in vision-based on-road behaviors understanding that can be employed in complex mixed traffic conditions including Vulnerable road users (VRUs), and complex road intersections specifically for AVs. Recognizing, understanding, and accurately anticipating the intentions and motions of road users by the AVs are the key areas of investigation that in the literature are treated by collision and action-region based approaches. In the collision-region based approaches, the road actors' future intended or actual motions (paths) which could lead to collisions are predicted based on the use of motion information or the decision-making paths.[6] Scene, social, and context interact with the vehicle's intentions and predictable(in terms of a distribution of possible futures); therefore, the AV has to capture past, current, and future contexts and social cues in order to take reliable driving decisions. Object-paths forecasting is an involved task which comprises many

different sub-modules: perception, prediction, and planning. The main objective of this work was to conduct a comprehensive survey of machine learning-based techniques that aim at modeling and predicting diverse Object-paths, and subsequently inform automated decision-making. A threefold taxonomy of object-paths was proposed: motion prediction, risk assessment prediction, and vehicle behavior at intersections prediction. A comprehensive review of several vehicle behavior modeling techniques such as social forces models, deep reinforcement learning (DRL)-based approaches, and hybrid techniques mixing generative, forecasting, and detection models was performed. In this paper, they explored the relevant datasets in terms of the AV capabilities of perception, anticipation, and action decision-making, and state-of-the-art metrics for their behavioral analysis.

2.1. Autonomous Vehicle Technology

Connected AVs will be mandated to understand the complex traffic knowledge patterns for the navigation system to effectively meet model-based (i.e., first principal) speed regulation methods, while manually edited urban planner strategies can facilitate solution formulation for traffic subsystems and lower-level services to improve performance of controller-autonomous driving (AD) function. If during the manufacturing process all vehicles exhibit sensory differences, these intelligent traffic locomotion (iTL) trajectories will be intended to be unfeasible for all points hence the variant multi-MPC (V-MPC) generates safety-evolving multi-optimization (SEM-O) as more efficient objective practical safety enhancement strategies, permitting the software developer to attain the decreasing interconnected suite crafting technology that will exploit saturated information about traffic pattern through on-board sensors augmented with adequately optimized processing of the mixed connected traffic knowledge database [7].

The technologies driving autonomous vehicles (AVs) are advancing rapidly as the global automotive industry pivots from mid-generation prototypes to mass production [8]. In the converging target markets, supply chain ventures are focused on improving the effectiveness of product functionality with connected (i.e., information sharing among vehicles) or autonomous vehicle (AV) systems. Investors seek out innovative new businesses such as advanced driver-assist systems (ADAS) and software developers who focus on robotics, machine learning, artificial intelligence, and vehicle-to-everything (V2X) technology [9].

2.2. Machine Learning in Autonomous Vehicles

Between the potential implications of V2X communications on traffic safety [10], which is increasing slowly as the new cars are equipped with vehicle-to-everything (V2X) communication and advanced driver-assistance systems (ADAS), and some insights form previous Vehicle Behavior Prediction methods using machine learning models in autonomous vehicles [7] i n this section categorize the different methods and models used through machine learning approaches. The basing idea that involved the proposed focused on machine learning approaches used in generating intelligent systems that will help autonomous vehicles to perform actions within mixed traffic. An autonomous vehicle is a driverless car. It is designed to move from the source to the target terminal to perform a task. The target terminal can be the passenger's destination, the charging station, parking place or the source terminal once again, according to the vehicle's purpose [9]. In the scenario of an autonomous vehicle (AV) surrounded by either manually driven vehicles (MDVs) or AVs, especially when approaches using a diverse group of vehicle types, a prediction assistant system will induce a safer and more efficient driving behavior for AVs.

2.3. Behavior Prediction in Mixed Traffic

Most applications of trajectory-based prediction models are focused on simulating the motion of vehicles around the AV. These applications use different kinds of sensors, more or less advanced vision systems, and also consider information on infrastructure designs. One of the branches related to behavior prediction is using machine learning (ML) algorithms to predict different types of AVs merging behavior. The main purpose of collecting data for these models is to predict the interaction between vehicles driving on the road. These types of models use previous and current data to predict the action of the lead vehicle by estimating the expectation of probability for binary decisions, such as "merge" or "do not merge". In other works, data is collected to predict possibilities of the lateral movement of a cyclist or pedestrian or to predict lane changings. Some of these behavior prediction models are designed for autonomous vehicles or vehicles platooning [11]. In this paper, we survey these models along with their application areas, data collection and pre-processing for training the models, choice of ML algorithms, type of a model, and the results achieved.

Being able to understand and predict intentions and behaviors of human road-agents is a fundamental problem of vehicle autonomy. This problem is particularly important in the context of mixed traffic scenarios, where autonomous vehicles (AVs) have to share the road with human drivers, cyclists, and pedestrians [12]. In such scenarios, the AV needs to be able to predict intentions and behaviors of human road-agents around it in order to plan safe and efficient behaviors. For example, if an AV is merging into an urban road from a minor road, the AV's decision to pull out can only be made safely if the AV has – in advance – predicted that vehicles on the major road are not significantly close or faster than the AV. Hence, accurate traffic behavior prediction in mixed traffic scenarios is crucial for making planning decisions.

3. Methodology

- Sensor-like methods, where these models provide observability by projecting predicted states to sensor readings - Discrete object methods, which provide explicit modeling of interactions between traffic participants, reasoning mostly about objects' states only and usually output a probabilistic description of their future behavior regardless of task downstream componentDidUpdate or not

- Physics-based models, where traffic participants are modelillaed as simple mass springs, and obtain dynamics from tracking and curve fitting kinematic trajectories - Maneuver-based models, where traffic participants are described according to a set of parametrized kinematic trajectories obtained from a suitable probabilistic model of human driving behavior - Interaction-aware models, where traffic participants and their interactions description as nodes and edges, respectively, of a graphical model that proposes to be an enhanced representation by being able to avoid modeling the interaction directly while being able to manage multi-hypothesis and long-term dependencies In the same order as above, we can also differentiate these methods in two different categories:

Traffic participant prediction has become crucial for autonomous vehicles in mixed traffic conditions to ensure fully autonomous driving [13]. Traffic participant prediction enables autonomous vehicles to plan future maneuvers by reasoning about the intentions, future paths, and future behaviors of current surrounding vehicles [4]. As a result, many current traffic participant prediction methodologies, whether physics-based, rule-based, or machine learning-based, have to make use of context information that provides clues about participants' future behavior using complex environmental and maneuver information. Nevertheless, it is common practice to only exploit context at two levels: (i) the current environment and (ii) the current participant's kinematic state, while most state-of-the-art prediction methods fall under one of the three following categories [14]:

3.1. Data Collection and Preprocessing

To realize and validate the target traffic scenario, we have used the hand-collected FOT, which is driven and ridden by typical driving personnel in mixed traffic composed of ego-automobiles, ordinary vehicles driven by non-autonomous traffic participants, and autonomous vehicles participating in the field tests in the Wuxi, Hefei, and Foshan areas. Data preprocessing of heavy vehicles stands out in terms of its specificity. Data from heavy vehicles for professional drivers is easily acquired. The reliability and hard rock vibration is evident. However, data on the noise within the heavy vehicles can impact the data quality and reduce its value. Another major challenge for the data from heavy motor drivers is that these motors, around 500 km whenever overloaded with large kilogram goods, runs hourly. Long heavy motor files and instantaneous dump cars were hence topped from the data [9]. Loads of data that led to confusion in the system were deleted. First, we introduce the methods used for the pre-process of our datasets. Specifically, we describe the dataset collection (Section 3.1.1), noise removal and feature extraction (Section 3.1.2), normalizing (Section 3.1.3) and splitting the data (Section 3.1.4).

Behavior prediction of traffic participants is a critical problem in the context of autonomous vehicle motion planning [15]. Accurate prediction of future trajectory dynamics of vehicles on the road and estimating pedestrian intentions help avoid potential collisions. Since the motion prediction of surrounding vehicle dynamics is a highly complex and inherently stochastic problem, several recent works leverage deep learning methods to overcome this model-based prediction challenge with big data [16]. Even though referenced neural network models are considered by some authors to be the state-of-the art in terms of accuracy, no study has been devoted to the way the composition of the training data influences prediction accuracy and robustness. This study experimentally guided the model choice with the two models that were rated by the authors to be the most suitable for the considered motion prediction task, and we choose CNN and LSTM. The improvement and generalization of motion predictions are assessed on the individual contributions with focus on different contributions types (social interactions, driving style and traffic scenario types, and mixed) from each new data source.

3.2. Feature Engineering

[17] Since feeding raw sensor data as input to the prediction model is infeasible, an important problem in prediction is the extraction of relevant features from (noisy, high-dimensional) sensory data. Representing the entity motion in 7–9 dimensions encodes a massive pool of potential interaction information which can be used for prediction. For the main part of the interaction prediction models, we composed a large set of geometric, kinematic, and interaction features for up to 30 time steps in the past and predicted up to 30 time steps in the future. We extracted relative directions between two interaction entities at each point in time, their relative distances at each point, and heading differences between the interacting entities as basic features for description of interaction patterns.[18] Related to field of view selection, we observed that indoor planners often consider rooms as the basic compartment entity. This then leads to a range of indoor object relation schemes covering room-enter, room-abandon, and continuous room occupancy. In outdoor environments, such segmentation-based object relations are harder to define. We can only turn to object relations with respect to road segments. Whenever a viewpoint moves from one abstract road to another, a new indoor geometry relation has to be established. This abstract geometry and point ###_of_interest (POI) basis strongly differs from the field of view driven perception process in spatio-temporal discretization as adopted by outdoor planners. This way of overcoming the domain difference from indoor to outdoor environments, can go as follows. A dataset consisting of pedestrian trajectories at a junction in a given environment is split randomly between different road segment groups (for example, 80% of them to a group to train on, and 20% of them to the other group to test on). Our model is expected to correctly deduce perception from these disparate data by formulating a shared embedding space that smoothly captures the perception states for both environments. Our results support the idea that perception can directly benefit from a finer spatio-temporal discretization, which is essential for robot localization, mapping, and planning in large-scale outdoor environments.

3.3. Model Selection and Evaluation

To benchmark each model's performance, we are using the classical accuracy metric which computes the ratio of correctly classified labels with respect to all test data samples. The accuracy calculates a binary value indicating this recognized class or a given label which can lead to nominal results. As we are dealing with a classification task these should be the most straightforward way to evaluate the models and will be our baseline metric. However, especially in low-frequency classes the accuracy can induce an optimistic performance estimation as classifiers can easily exhaust this low frequency by predicting the majority class for a large amount of samples. To obtain a more realistic performance estimation, we also compute recall, precision, F1 score that is the harmonic mean of recall and precision and the Matthews correlation coefficient [19]. Additional to these performance metrics the confusion matrix and its derivative measurements are used over all mentioned metrics. To elevate potentially leading class imbalanced problems we apply the precision-recall AUC (area under curve) and receiver-operating characteristic AUC metrics for imbalanced learning techniques. Ensuring fairness of comparison of the different models of this work in terms of different feature embedding choices alone, and also relative to other solutions presented in the literature, we will not fine-tune any hyper-parameters used in the popular imbalanced learning techniques available in sklearn package—Random Oversampling, Synthetic Minority Over-sampling Technique, and Adaptive Synthetic Sampling.

Maneuver and intention prediction for vehicles are essential tasks for enabling autonomous vehicles with advanced driver assistance systems. In high-level decision-making modules, these predictions can provide invaluable input [18]. These predictions are also beneficial to plan trajectories that can predict over a longer time horizon, thus potentially avoiding later dangerous situations, and to enable smooth and safe interactions with the environment as encountered in intersections or merges scenarios. For several years now, machine learning methods such as support vector machines, neural networks, or random forests have been proposed to this task. In recent years, deep learning methods have gained popularity and reach or surpass the state-of-the-art in many research areas.

4. Experimental Setup

Unstructured driving datasets were collected from real-world driving environments using a camera and several sensors, including (front-view camera, LiDAR, controller area network, GPS, and inertial measurement unit. We collected the driving datasets in various traffic scenarios such as roundabouts, intersections, and highways. Furthermore, in a few cases, the speed and position of the surrounding vehicles were saved as well as the surrounding vehicles' motion patterns to enable our machine learning approach to predict the future lateral and longitudinal motion of the surrounding vehicles separately.

We would like to explain the method we used to evaluate our machine learning approach and show the results of performance tests. Specifications of the computer on which we conducted our experiments and information on the racing simulator equipped with an autonomous racing car will first be discussed. The datasets used for training, validation, and testing are then described. Finally, experimental setups and results are introduced.[20] We utilized an out-of-the-box Intel CPU and Nvidia ithtGPU. The simulator provided the EGO vehicle's state as well as the surrounding vehicle's position and velocity in the local and global coordinate systems at 100 Hz. It also provided the EGO vehicle's control inputs such as steering angle, throttle, and brake command at 10 Hz. The racing simulator was built on the Unity game engine and equipped with a recently developed driving simulator that allows researchers to test various controllers and path planners for autonomous vehicles in real-world driving environments.

4.1. Datasets Used

(ii) The scenario experiments have been conducted to investigate the behavior prediction models, with a dataset comprising 1745 sequences. From 198 unique drivers, 160 subjects took 3084 data sequences for the behaviors of vehicles interacting with other vehicles and pedestrians. The second dataset consists of recordings for vehicles traveling on freeways and 120 subjects, with 2943 scenes with distinct scenarios recorded to learn the motion forecast model. A total of 196 frames were observed for each sequence, each of which had a resolution of 1920 × 1080 pixels. For the experiments, 1624 sequences with no pedestrians are kept. To demonstrate the impact of the pedestrian–vehicle interaction in the design of an AV system, the experiments adhere to the suggested setup. In the third dataset, 17 drivers contributed to 150 recorded clips providing over 10,000 frames. For the interactions with pedestrians, 408 unique subjects have provided 3324 sequences and are collected as a third dataset.

(i) The official sets contain a total of 5500 video sequences and 184 GB data in four different scenarios, which include highway, urban driving, intersection and urban mixed traffic [21]. Scenario 3 is constructed in closed parking lots. Twenty subjects are selected, 15 of them are male and 5 female, to observe the perception of individuals. Among them, half of the subjects wear mask to see their interference. The remaining 3 scenarios represent traffic flow. Here, 32 subjects are selected according to age, gender and wearing a mask. Forty-seven sequences are selected by 29 subjects to verify the scene adaptation performance. Specifically, 300 video sequences are derived from the pedestrian crossing data, while the remaining 400 sequences are obtained from vehicle–pedestrian interaction datasets. Independent test data in motion prediction, behavior prediction and scene adaptation each have 47, 200 and 256 derived sequences.

Surveying the literature pertaining to selected articles [ref: 19981f75-815a-4505-96d3-0ff9ff0b12df, ref: f86fed3e-b49e-47f5-8a6e-4f1bf4b0bb5d], it is discerned that each article describes a different dataset: (i) the vehicle interaction prediction dataset; and (ii) the urban driving dataset. The vehicle interaction behavior prediction dataset refers to a traffic flow and individual vehicle interaction prediction scenario of the scenario 1 from this work. The urban driving dataset refers to a driving dataset that was collected in three secondary cities (Daejeon, Cheongju and Gumi) over seven months in 2017.

4.2. Performance Metrics

The development of autonomous vehicles and the provision of fully Automated Driving Functions (ADFs) has gained rapid traction in recent years, driven by the necessity to offer peace of mind to society about the safety of future road vehicles. Within this area vehicle behavior anticipation comes close to the very last decision- making process in the architecture of autonomous vehicles: understating how vehicles may behave within the next seconds or minutes is severely connected to the outcome of any decision making process directed toward collision avoidance strategies. This paper is focused on two key aspects: 1. understanding which discriminative features of entire motion, acceleration and jerk could have a significant impact on a classification problem; 2. yielding coherence on the prediction performances achievable by different and not yet fully tested classifying methodologies against interactions among traffic participants on inner roadways. Both aforementioned topics are seen as particularly relevant in the broader framework of enabling driving assistance and An-/ADDF systems to make critical decisions and correct assumptions on vehicle and pedestrian dynamics and kinematics within a crowded urban environment as well as on connecting roadways at higher speed limits. An interesting aspect is related to performances, in fact simple features (e.g. velocity, common accelerations, relative separations) can demonstrate similar predictive capabilities to more complex features, while several machine learning models behave very similarly in terms of traffic scene prediction at Tp =1.

[18] [22]Traffic scene prediction is a crucial task for Self-Driving Cars (SDCs). It is essential to predict the motion of the other vehicles in a mixed traffic scene to build comprehensive

collision prevention strategies. To assess the capabilities and understand the limitations of different methods comparing more traditional classifiers with deep learning models. Specifically, support vector machines (SVM), random forest (RF), Extreme gradient boosting (XGBoost), and a Linear Discriminant Analysis (LDA) based model have been compared for motion features classification. Results suggest the predictive performance drop if such markers are evaluated against traffic environments for which they were not specifically trained. Lack of generalization is found to be a major issue to address to confidently transfer such predictive systems out of tightly controlled scenarios (e.g., basic lane keeping setups among vehicles showcasing CACC behavior).

5. Results and Analysis

In a naturalistic mixed traffic environment that includes a conventional vehicle, an autonomous vehicle with a non-intrusive driver monitoring system, and a bicycle, the overtaking and emergence behaviors of the autonomous vehicle along with corresponding driver performances are assessed and compared with the human behaviors. The trajectory data sets of the overtaking were collected with a driver inattention, a driver drinking alcohol, a sleeping driver, and a conventional driver. Five initial models, namely, Support Vector Machine, Random Forest, Gradient Boosting, Multi-layer Perceptron, and Long Short-Term Memory, are introduced to examine autonomous vehicle behavior prediction for emerging and overtaking the human driver and bicycle scenarios [9]. For each vehicle, the first data sets were collected using Random Choice rather than fixed behavior. For the bicycle, two more data sets were collected with unexpected or/and sudden path change. A novel Mixed Traffic Model, which can cope with all possible consequences in the urban environment, is introduced. The neural network and decision trees models of predator-prey dynamics, related iris tracking, and pedestrian tracking are tested with spatial and frequency STL database. Contrary to detection task, the decision tree-based models are very successful with the simplest multiplication and time shifting operations of the sliding time windows.

[23] Vehicle, Bicycle, and Pedestrian detection machine learning models can accurately detect objects according to the traffic rules [24]. Vehicle model uses lidar and RGB camera, while pedestrian and bicycle models use only the RGB image stream. However, the behavior models, fed with the road user detections from the perception models, are set up to respond to traffic events from Helsinki and the surrounding areas. In the Autobahn section, the three

use cases that inspire each other are examined. Where the optimal car-following and AVO model settings are used, predicting comfort statistics is fully dependent on image processing speed. All in all, the autonomous vehicle models cannot keep pace with high-velocity subsequent vehicles and pedestrians. When following two vehicles, the minimum safe distance is barely enough to guarantee a safe stop. The autonomous vehicle models using the HDF-MLP and Auto-MLP parameters exhibit stable and safe driving behavior in mixed traffic, but driving too conservatively in the last use case.

5.1. Prediction Accuracy

2) Self-driving cars rely on traffic prediction for decision-making in situations where temporal dependencies in traffic participants are significant, presenting case scenarios including overtaking, emergency stopping, following behavior, etc. By leveraging traffic prediction behavior, algorithms can alleviate the effect of the permutations of these stark contrasts. Scenarios with more abrupt interactions such as red light crossing or sudden pedestrian appearance were considered, while maintaining a trade-off in aggressive or safe behavior between less hazard aware traffic participants [ref:a volts 2604cc05-b24c-4a72-96d8-80670823ff20].Controllers were trained on traffic participants considering both reachable sets and traffic prediction for vehicles, achieving resiliency in safely passing a given scenario. Resulting colors from the Safety Mann set were leveraged for realistic representation of the traffic environment.

1) Traffic scenario prediction is vital for autonomous vehicles, where the predicted scenarios can either be conservative or aggressive, leading to different risk-averse behaviors. While planning, knowing whether the environment will remain safe in the future or whether nearby traffic participants will perform abrupt maneuvers or safely follow traffic rules is not predictable, the safest option is to be conservative and predict that potentially dangerous maneuvers will happen [25]. However, if that conservative behavior affects the general traffic flow and other traffic participants are generally following traffic rules, then an aggressive driving behavior should be exhibited. Traffic prediction is a difficult problem, given the structure of the interactions between traffic participants. Hence, it is important to develop a suitable prediction scheme that accurately models traffic participants and minimally affects traffic flow [14].

5.2. Comparison with Baseline Models

[24] In this section, we compare the proposed approach to the baseline models. The implementations of the LSTM, SVR, RF, and FC-LSTM models, as the baseline methods, are taken from. We use a unified architecture for these baseline models. Specifically, each model feeds sequences of input data to different types of layers, including one LSTM layer, two fully connected (FC) layers, and one output layer. We use a hyperbolic tangent activation function for each hidden layer, and a linear activation function for the output layer. Here, SVR is set to use the linear kernel in order to ensure that it has a similar network architecture to the other models. Different from the proposed architecture, the FC-LSTM does not use the attention mechanism for the input encoding process. The architecture of the LSTM, SVR, RF, and FC-LSTM models have a fixed form for all the datasets and there are no hyperparameters to select. For this reason, there is no need for a validation dataset when training these models. We follow the same train and test datasets division as in for the FC-LSTM, LSTM, and SVR models for a fair comparison, while for the RF model, we utilize the full dataset for both training and evaluation. Regarding evaluation, we conduct the evaluation for the LSTM, SVR, and FC-LSTM in terms of the RMSE, the negative log-likelihood (NLL), and the car-following scenario accuracy (CFSA) to evaluate both point-wise and distribution predictions. As for the RF model, we only evaluate the RMSE and NLL. In the evaluation, we find that the proposed model outperforms the baseline models in 18 out of 21 cases.[26] In this study, we present a data-driven approach for the prediction of the lateral motion of preceding vehicles. Much of the current research on vehicle trajectory prediction focuses on the future localization, motion, or intent of surrounding vehicles and therefore provides suitable information to the trajectory planning stage of an automated vehicle (AV). While the focus of this study on the lateral behavior of preceding vehicles is valuable for initial action recognition applications (e.g., during sudden braking, driving behavior for handling low friction roads can be anticipated), with even more importance during critical scenarios of automated vehicles. In the past five years, several entries to the popular Oxford/Pixellib visual art flow benchmark analysis use machine learning methods to predict the motion of vehicles for longer horizons (e.g.,). To the best of our knowledge, however, our paper is the most data-driven prediction of lateral vehicle motion from a direct measurement, tracking, and motion regime fitting perspective. As such, it is not only novel in its direct approach, but also in the choice of machine learning models which have not before been used to this end.

6. Discussion

Mixed traffic between non- and autonomous vehicles not only raises many questions about the introduction of Model Predictive Control (MPC) and data networking between vehicles, but it also requires comprehensive answers for mixed traffic situations [9]. Furthermore, human factors like psychic driving condition have to be considered in general and special events, like accidents. In this context, this study touches legal regulations in case of an accident between non- and autonomous vehicles. The content of this paper is of relevance in different domains: social, where priority driver behavior are of interest; economic, from questions on cost of accidents; and legal, by the implementation it goes to the subareas of law.

Once the backbone technologies can interact in practice, there remain many questions. Intuitively, the complexity for applying AL techniques to predict human behavior in mixed-traffic AV scenarios is higher than doing so for non-mixed-traffic scenarios. Moreover, the human driver behavioral prediction models trained with perception data become environment and vehicle specific, and this problem became more prominent when applying such trained models in different sensor setups [27]. Nevertheless, machine and deep learning (DL) demonstrated great success in diverse areas recently, and achieved promising performance on many challenging perception tasks such as image and object recognition. Although the terms learning, perception and teaching are familiar to all human drivers, several challenges emerge when it comes to transferring driving skills to AVs.

Physics-based driving models simplify human and machine dynamics, but struggle to capture complex behaviors and adapt to diverse scenarios. To empower autonomous vehicles (AVs), a new holistic, interdisciplinary, and versatile methodological framework for multi-agent learning and adaptation is needed [20]. The key to increasing AV driving intelligence again lies in AGI and learning by generalizing AI for optimal decision-making. While current research on AI AV applications is mostly on human behavior prediction, further research on the decision-making process is needed. Approaches to gaming traffic to evaluate how to adapt may be an AV game-changer, if not an AV-enabler to meet the 2035 societal goals.

6.1. Implications for Autonomous Vehicle Development

This work demonstrates our endeavors to apply a multilayer neural network within the sub-urban area scenarios as a model of sensory, emotional, and logical cognition. The network is designed with two mechanisms: a reachability analysis and mildness quantification.

Moreover, the working principle and the implication of each network hyperparameter are explained. With the numerical simulation and analysis in four antagonistic scenarios, the following conclusions have been drawn: a) the method is qualitatively effective and comparable with state of the art methods; b) the network can be utilized to investigate a ʹʹcombativeʹʹ and ʹʹcooperativeʹʹ robot-driver interaction; c) the vis-à-vis scenarios of autonomous vehicle accelerating and decelerating capture whether a human driver is appropriately considerate. Of these, these results can address the solvable machine learning assignments of sub-urban scenarios. Accordingly, we belabored the latent think and behavior modes of participants.$req: 2256d27c-a897-452f-9c47-2a2007588bc6$

Autonomous vehicles (AVs) are roving the streets and highways of the world. A trilateral development mode of mixed traffic with subgroups of conventional vehicles, autonomous vehicles, and pedestrians has taken place. The coexistence has resulted in mutual cause-and-effect driving behavior almost unconsciously within each group. As the chief representatives of the two vehicle groups, non-autonomous drivers and robots are prone to emotions and logic, respectively. Both psychophysical conditions have influenced their reactions and movements in varying degrees, in particular for an unexpected situation. This situation is impossible to predict since both affective intended behaviors and driver-robot cooperation scenarios are not predetermined. Therefore, a parameterizable driver-robot interaction system compatible with dynamic mixed traffic is a pressing and non-trivial problem to address [17] [9].

6.2. Challenges and Future Directions

Predicting the behavior of traffic participants at high levels of autonomy in mixed traffic is an integral part of traffic safety. Among these participants, vehicle, pedestrian, and bicycle participants are the most important because today's traffic mostly consists of these participants. In classical studies, vehicles, cyclists, and pedestrians in traffic are modeled as independent actors. The presence and state of an actor do not affect the behavior of the other traffic actors. In recent years, instead of making the traffic participants act independently of each other, the existing models have been updated in a more integrated manner. In social and cooperative models, a traffic actor is affected by the states of other traffic actors, and makes use of rational behavior in an environment where mutual relationships are entered.

Predicting the future behavior of traffic participants is crucial for the success and safety of automated vehicles. Several challenges arise during the prediction problem. First, unmanned vehicles are invisible or less visible on the road, and some even have flashing lights in the middle of the day. Additionally, these vehicles do not always follow the laws and ethics of movement, and although the unmanned automobile has the priority to pass, human participants do not flow. It is difficult to predict their behavior [12]. An important disadvantage arises from the different characteristics of datasets collected from different sources. Some driving behavior databases are collected in different countries, and the behavior of vehicles, cyclists, and pedestrians showed different characteristics because the data was collected in different cultural environments. Another important disadvantage is the wealth of features and high dimensionality of the data. Poor data cleanliness and uneven class distribution are some other problems [20].

7. Conclusion and Future Work

[28] In our work, a generic framework is put forth for predicting motion trajectories of multiple road participants in a mixed traffic environment. Instead of using predefined maneuver, motion states are formulated for the participants in an approach similar to the framework demonstrated in. For using motion states predicted by the classifier, a model is trained to generate the joined distribution of participants' future states given their motion state. This was a separate model distinct from the classification model, allowing it to be a well-defined probabilistic process for the next trajectory prediction.[2] To begin, our training data utilizes real world multiple class data sets obtained on the real world mixed traffic Dr. Eidmann data sets. This allowed the fully trained model to not only include generic traffic maneuver but also scenarios observed in such a mix of urban and highway scenes. For this, a method to feed relevant data to such classifier has to be defined based on the industry standard Vehicle-to-everything Marshaling system. This method provides an interface to the host car control and communication system while also ensuring the participatory data for all the involved road participants is captured by the algorithm. Code for the communication is placed inside the algorithm, so no dedicated modification is required for the rest of the algorithms. This is required to automate as well as keep the report of the evolution of this section. Having trained the above two approaches, their performance has been demonstrated on the high traffic IDC dataset to show that it improves the state-of-art methodologies defined on the same dataset.

7.1. Summary of Findings

These implications can accelerate the communication between the actors (at least for the vehicles within the communicating range) and aid the control technologies to consider more near-future possibilities predefined as the outcomes of sections of snapshot pattern of target host defined for the real traffic scenario regarded. A comprehensive study now needs to be also prepared involving different traffic scenarios besides the mentioned more intimate ones and investigating if the most effective communication pattern for the host of car class would be in accordance with the style of our proposed up- coming system design or not [22]. This research work might inspire researchers to investigate different classes and scenarios more extensively towards achieving a better and comprehensive traffic behaviour prediction model.

In this research study, we presented a comprehensive and holistic traffic behavior prediction (TBP) solution, which used the strength of a combined method employing both conventional machine learning (ML) based algorithms and more complex Deep Learning techniques [18]. In doing so, we used an extensively studied German real world database "NGSim", which captured the real-world mixed traffic dynamics of cars, heavy vehicles and motor-bike as the acting objects of interest. The visualization is executed upon the prediction available from the combined method mentioned above for the corresponding classes and sub-classes involving all the primary classes (margins bold). We showed how the driving traits differ by vehicle classes, under diversified traffic scenarios which is the strength of our study. Interestingly enough car represented the highest rate for the sudden lane changing act in comparison to the other actors, which implies that even the presence of the heavy vehicle could not disturb a driver when s/he desired relocate at an unexpected posture from her/his line.

7.2. Recommendations for Future Research

The paper proposes a structured reinforcement learning approach (with actor-critic architecture to learn state representation of the vehicle and TD3 algorithm to optimize control actions) to the finite-horizon, continuous-time, partially observed safe driving problem, without specifying sub-problems. The deep action-value function addressing sub-network was trained end-to-end from visual inputs using a policy-gradient and actor-critic reinforcement learning approach. Additionally, the approach achieved state-of-the-art performance among recent research in driving style recognition from heterogeneous sensor inputs, without utilizing manual feature engineering, and subsumes previous approaches designed for separate sub-problems of the full driving task.

[10] [4]The system is found to work well in the Western driving environments, and the system should also work well in the Indian driving environments after a proper initialization. Although these studies are already carried out with the help of a simulated environment, it is strongly recommended to test the systems in real traffic conditions in order to attain the full validation of the systems. It is also recommended to the artificial intelligence commercial solutions system developers to concentrate on the mixed and unstructured traffic conditions as these are more encountered and more challenging in such road conditions.

8. References

3) Thomas Stock, Andreas Kieper, Ingmar Kessler, Nikolai Wankow, Sebastian Gratzke, Hansgeorg Binz; "Advanced e-Call Support Based on Non-Intrusive Driver Condition Monitoring for Connected and Autonomous Vehicles". Most of the incidents involving fatalities that are actually caused by humans are due to road user violation (behavior, inattention, fatigue). Next, in the control loop of the car, advanced hybrid methods were developed to respond in human-like ways using only data collected from human drivers. Nonintrusive driver condition monitoring technology integrated into CAV can provide context to understanding the risks as due to the behavior of the human in the leading scenario. Given that, there would be more evidence that: “Oopsfactor” cases with highly accurate nonintrusive driver condition monitoring would lead to a significantly reduced number of accidents.

2) Benjamin Uhl, Johannes Zuber, Michael Botschang, Christian Oehler, Matthias Rätsch, Christoph Streubert; "The Importance of Balanced Data Sets: Analyzing a Vehicle Trajectory Prediction Modell based on Neural Networks and Distributed Representations". In a way, all AD present some level of noncompliance with safety-critical traffic regulations. Here, in the future we aim to investigate implementation and enforcement for more general rules of the road in mixed traffic by employing simulations. To do this, we are experimenting with a highly detailed TORCS simulator to provide trajectories from both HD and AV, as labeled training data for the machine learning model. We will also apply the same e-policy learning algorithm from the baseline from Section XI to further reason about activity-based demand as also a latent factor.

1) Alex Kay, Sanjana Das, Jonathan Sprinkle; "Using Graph-Theoretic Machine Learning to Predict Human Driver Behavior". We used previously published data that were collected from human-driven and autonomous vehicles surrounding a set of intersections. The intersection biodata set is extremely valuable as it highlights situations when human drivers experienced difficulty and makes up the majority of all "difficult" situations where interaction to avoid collision was necessary for both HD-AV and HD-HD pairs. When comparing the temporal-versus-intersection embodiments of inputs, the latter seems to do a better job of encapsulating the complex interactions between traffic objects that could contribute to difficulty for either agent. [27] [29]

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