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Learning-Based Conceptual framework for Threat Assessment of Multiple Vehicle Collision in Autonomous Driving

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Abstract—The autonomous driving is increasingly mounting, promoting, and promising the future of fully autonomous and, correspondingly presenting new challenges in the field of safety assurance. The unexpected and sudden lane change are extremely serious causes of traffic accident and, such an accident scheme leads the multiple vehicle collisions. Extensive evaluation of recent crash data we found a crucial indication that autonomous driving systems are most prone to rear-end collision, which is the leading factor of chain crash. Learning based self-developing assessment assists the operators in providing the necessary prediction operations or even replace them. Here we proposed a Reinforcement learning-based conceptual framework for threat assessment system and scrutinize critical situations that leads to multiple vehicle collisions in autonomous driving. This paper will encourage our transport community to rethink the existing autonomous driving models and reach out to other disciplines, particularly robotics and machine learning, to join forces to create a secure and effective system.

Index Terms—Robotics, Artificial Intelligence (AI), Reinforcement Learning, Autonomous driving, Multiple vehicle collision, lane change, threat assessment.

I. Introduction

Autonomous vehicles (AVs), which provide comfort in driving, road safety and other services, would build the foundation of future Intelligent Transport Systems (ITS) of next generation [1], [2]. The self-driving car called an Autonomous car is the core concern of contemporary technological fields such as AI, robotics, IoT, Machine learning, Reinforcement Learning [3]. In the prevention of traffic accidents, real-time crash risk prediction is expected to play a crucial role. World famous business giant and leading companies such as Google, Tesla, General Motors, Uber, Ford are a common name that is trying to develop an autonomous car technology [4]. They intend to plan to lead the next automobile market. The contemporary autonomous driving system is a cognitive and Instant combined reaction of its three actuators a) Steer, b) Brake, and c) accelerate. Potential research works are confronting for the optimal combination of these three actuators tasks. A perfect detection technological arrangement is the key factor to prevent upcoming critical collisions [3]. A variety of critical metrics are proposed for threat assessment, and an appropriate critical metric is crucial to pick to deal with particular driving tasks under various driving conditions. Critical metrics are categorized into five groups, i.e., 1) time-based, 2) kinematics based, 3) statistics-based, 4) potential field-based, and 5) erratic driving behavior based metrics. We reflect a learning based threat assessment approach to erratic driving activity by deploying a comparative analysis of state-of-the-art critical metrics focusing on real-world validation of driving results.

Figure 1: Symbolic pattern of a multiple vehicle collisions caused by uncertain blockage

Though researchers are continuously trying to make an enjoyable vehicle journey with minimum difficulties. However, in some critical cases, the respected researcher overlooked or unexpectedly missed risk assessment issues that lead the multiple vehicle collisions. Most existing research works only focus on collision with single or twin vehicles that are considered a single-vehicle collision. They usually ignored the multiple vehicle collision risk factors that are common real-time crash risks in the urban arena.

Multiple vehicle collision typically a collision among several cars in the road traffic. These are some of the severe types of accidents that occur on high-capacity and high-speed roads, such as highway. Another big cause of accidents is adverse weather, which often leads to collisions involves many vehicles. There are some serious cases of multiple-vehicle crashes [1], [5] and symbolic presentation shown in figure:1.

We found a broad evaluation in the form of physical models of multi-vehicle collisions by T.Nagatani et al. in [6], [7]. They investigated:

1. Multiple-vehicle collisions caused by an abrupt evasive maneuver to shift the lane.
2. Sudden slowing trigger multiple-vehicle collisions.
3. Multiple vehicle collisions caused by Low visibility [8], [9] and cyber-attack i.e., Spoofing Attack, and Jamming Attack [10].

Contemporary researchers and academics are trying to establish a proper theoretical aspect of preventing multiple vehicle collisions both in the domain of non autonomous and autonomous driving systems [11].The investigation in this direction proposed different approaches: (a) Practice the one car-length rule (b) Make sure extra distance for stopping in bad weather and when driving a large vehicle (c) Always be prepared to take evasive action (d) Stay focused on the road (e) Eliminate distractions while driving. During the past two decades, there has been a well-development in the sensing mechanism (perception), vehicle control [12] and communication [13] technologies. [14]. Multiple vehicle collision avoidance and control strategy, however, present unified challenges due to restricted navigation and unpredictable curtail traffic conditions. Learning-based methods such as machine learning, deep reinforcement learning is evolving as a likely approach to autonomous driving policies that can deal with these challenges.

In this work, the safety-critical situations are classified intuitively from multiple vehicle problems encountered by a perfect maneuver-planning framework into three distinct cases. Finally, we propose a conceptual framework for assessing the threat in terms of multiple vehicle collisions.

1. Make it clearer what caused the multiple collisions in vehicles. It is more critical than the current framework for improving the safety capability of autonomous vehicle driving systems.
2. Propose a conceptual framework for threat assessment of multiple vehicle collisions in the domain of autonomous vehicle in terms of critical condition such as uncertain lane change driving behavior.

As per our knowledge, no research work provides sufficient directions to assess and prevent this problem. So, the significant lack of realistic approaches to solving this difficult problem leads the contemporary researchers and academicians to establish a proper theoretical aspect of preventing multiple vehicle collisions in the field of autonomous driving. The remainder of this paper is structured as follows: In section 2 we summarize the characteristics of similar work. Section 3 represent the outlines of the conceptual framework and Section 4 presents our observations, as well as the implications of the analysis, drawbacks, and suggestions for future studies.

Secondary collisions often lead to multiple chain collisions where a sudden lane shift caused the first collision. When a driver on a two-lane highway switched from the first lane to the second lane, multiple vehicles collided. On the first lane of the second lane, if a car reaches a high speed, the second lane of the forward vehicle will crash, and the crash will lead to more collisions. [15]. Another believes that because of road work to boost heterogeneity, the 3-leaned highway is reduced to only a single lane or the leading vehicle unexpectedly stops by a blockage. These signs warn vehicles to slow down to 70 km/h and merge into a single lane afterward. This traffic conditions leads to a more complicated scenario, potentially making more noticeable differences in the controls. Under fog weather conditions, multiple vehicle crashes occur easily. J.Tan et al., [16] demonstrate the impact of space headway misjudgment on the collision among several vehicles in a traffic flow. More deep evaluation of the causes of the first collision that induces secondary and multiple collisions can be found in [17], [18]. Figure: 2 represents the deep illustration of multiple vehicle collisions caused by abrupt lane change.

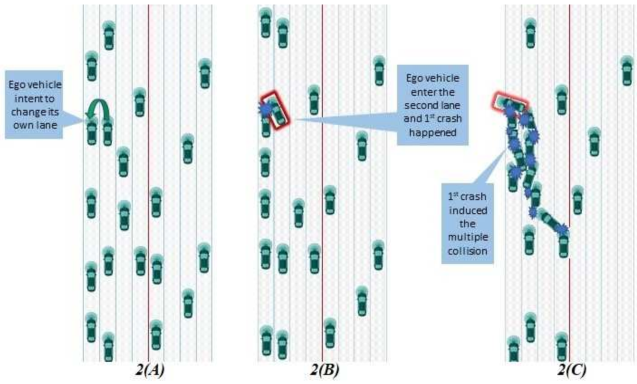

Figure 2: Symbolic pattern of a multiple collision of vehicles caused by where in 2(A) ego vehicle intent to change its left side lane, 2(B) ego vehicles changed its own lane and 1st collision happened, 2(C) the 1st collision of left side lane triggered the severe multiple collisions.

II. Literature Review

Threat assessment (TA) methods can be divided into two groups in the existing literature, such as 1) based on physics and mathematical model, and 2) based on data driven models. Authors of [19] performed a gaze driving behavior in the virtual simulator environment by using Artificial Neural Networks, Na¨ıve Bayes Classifiers, and Bayesian Networks. The perfect threat assessment methods the time to collision (TTC), inverse TTC (ITTC), time to lane crossing (TLC), inter vehicle time (IVT), time to maneuver (TTM), time to brake (TTB), time to steer (TTS), time to kick down (TTK), time to react (TTR) are the common basic elements in time domain threat metrics. In the Acceleration Domain A) steering threat number (STN), and B) brake threat number (BTN) are the core concern [20], [21]. The concept of minimal safe distance (MSD) is commonly used in the distance domain. In a more complex situation, no single method is enough to mitigate the collision, and hence the author [22] employs the combination of two or multiple methods in a method that we called Multidomain. Regarding solving deep complex critical situations, researchers invest contraction on formal methods. With a combination of machine learning models and optimization techniques, data monitoring performance is improved. Using these methods and detection of reckless driving behavior is now more accurate and effective [23]. Machine learning techniques have recently become prevalent for various tasks in ADAS and fully autonomous vehicle applications. The rapid development of computational power and device algorithms that are enthusiastically funded by major companies such as NVIDIA and Intel are for evaluations where input is the current state of any system and the output is a prediction of the future state of that state. Interested readers can be referred to Read [24] for further information on learning methods. Potential work to predicting the next state frame of any video was Comma.ai, which was the combination of a varying Auto-encoder (VAE) and a Generative Adversarial Network. In several scenarios, video prediction gives an ill constrained as the previous action. An interesting technique to consider in this situation is Imitation learning, which idea has previously been employed in various events involving autonomous flight, articulated motion, modeling navigational behavior, road following, and off-road driving. The demonstration of Google DeepMind games such as Atari and Go, the approach of deep reinforcement learning (RL) is concerned with recent researchers. Here The scheme is that the model training process performed by a predefined reward function due to confirm correct learning from past. In terms of mapping driving behavior, such as the current steering angle, lane change, and lane-keeping, from acquired images. The method of direct perception applies to CNNs, where the main perception measures are defined [25]. Another suggested deep learning approach focused on deep autoencoders and stereo vision to identify obstacles on the highway [26]. The elaborate discussion on Artificial Neural Network (ANN) reader is requested to see [27]. Further authors use the recurrent neural networks (RNN) and support vector machines (SVM) techniques to predict the driver behaviors specifically for lane change and lane-keeping scenarios. Unfortunately, a limited number of transportation safety professionals and researchers have been implementing data driven models as a popular modeling framework for Multi-vehicle crash analysis and risk estimation in the autonomous domain [28], [29]. There have been several research attempts to predict the risks of crashes using physical models such as [30]. Researchers are trying to make it a highly reliable intelligent system that can promise safety every bit of the time [11]. However, avoiding a collision between these vehicles and human driving vehicles are absolutely remains perplexing for autonomous vehicles system. Contemporary sensors of autonomous vehicles (AV) are mounted and have exploded quantities of transport data. A significant amount of study was done to determine driver performance in dilemma environments, which is skeptical and lead to a right angle or rear-end collision [31]. While traditional learning frameworks are good for imitating the actions of human drivers, they take huge time and error because human experts create them. Since deep learning is increasingly difficult, the architectures are difficult to build by hand. For these considerations, different studies were conducted to automatically generate network architecture. Structure Learning is a useful method that allows an artificial neural network (ANN) architecture to be found automatically. That is why ANN topology is generated with the structure-learning algorithm. However, because of the absence of sequential data, NAS based DNN is still challenged. To sequence the sequence of a string, which encodes the neural architecture Zoph and Le [32] use the recurring Neural Network (RNN) policy. The key benefit of RNN over ANN is that RNN can be model a data string (i.e., time series) to ensure that each sample relies on its predecessors. Hand-made RNNs are implemented in this document to convey sequential data in both the acceleration and deceleration situations.

III. Framework

To propose an exceptional framework for assessing a dynamic agent's safety and detecting all the safety-critical situations in a distinct environment this framework can be employed to visualize and expose the threats of the mysterious critical situations that may be detected by a reinforcement learning agent with an appropriate set of iterations characterized by the application designer. Autonomous systems operating in complex, dynamic, and interactive environments require RL techniques that generalize the interactions with multiple traffic participants to unexpected situations and rationales timely. In difficult situations, such as adverse weather conditions, this technology still achieve human-level trustworthiness in perception, planning, decision making, and current detection, and segmentation precision is not yet adequate. Trajectories of any identified vehicles are not deterministic in autonomous vehicle driving systems, while they are affected by the environment, the driver's destination, and driving behaviors, which increase the difficulty of avoiding collisions.

A. Outline of the framework

In this work, we consider and make a conceptual threat assessment framework to investigate the unexpected driving behavior-based on uncertain lane change conditions, which are the main causes of 1st collision, and if the leading car and following cars are at high-speed then the 1st collision whether or not lead to the second collision, the third and multiple chain collisions. To build a proper framework for multiple vehicle collision prediction systems, there are two important aspects: 1) threat assessment or detection and 2) risk quantification of a dynamic autonomous system is essential. In this work we investigate only the unexpected lane change condition elaborately under our cognitive framework to make sure a better understanding of collision threats. We investigate whether multiple vehicle collisions are stimulated by the first collision or not. With the help of Reinforcement-learning

Table: 01 (Aspects of a TA conceptual framework)

Autonomous Driving Segmentation	• Strategic • Tactical • Operational
Our Targets	•Identify attributes that define the domain of operational design. •Identify the sensing and reaction capabilities of objects and events. •Identify and analyze modes of failure and methods for reducing failures.
Concern features	• Physical Structure • Functioning Constraints • Connectivity • Objects • Environmental Situations • Participants (Multi agents)
Detection options	• Abrupt moving out of travel lane or suddenly enter another lane from the current lane.
Evaluation cases	• Abrupt lane change operation
Workflow (future research options)	• Modeling and Simulation. • Closed-Track Testing. • Open-Road Testing.
Dataset (future research option)	Next Generation Simulation (NGSIM).

model and finally the threshold values will be investigated, these values were investigated in a physics-based model by T.Nagatani et al. [6].

B. Architecture of threat assessment Framework

This section represents the framework to predict the sudden lane change composition in an unpredictable, mixed-integer state of an area in which many cars pass parallel to another lane. The arrangement of the frame comprises four modules and is presented in Figure: 3. A calculation model, the planning center to address the situation prediction model and the reward form, takes account of the uncertainties in the transformation of measurements into state projections.

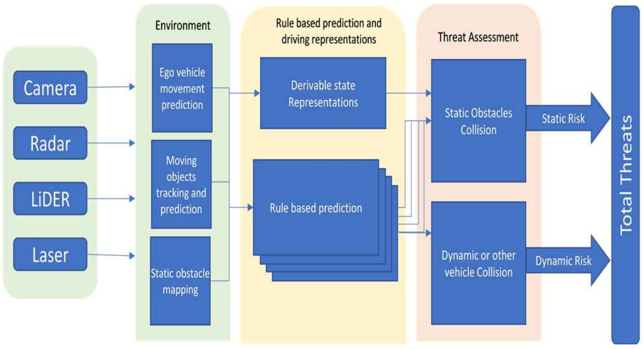

Figure 3: Proposed Autonomous driving threat assessment framework

1) Target Lane: Vehicles generally use two driving behaviors in highway situations described as lane-keeping and changing [33]. In the elaborate sense, the vehicle in the roadway drive contained by a lane or except for a lane change. For these drivers have an aim lane, in our framework, the system feature will be able to monitor the lane-keeping or changing the decision of ego vehicle [34].

2) Lane Change Possibility Estimation: The reinforcement learning-based framework must be capable of estimating the lane change possibility of the ego vehicle in any dynamic situation where multiple vehicles are present in both the ego and right-left sides of the ego lane. The number of lanes in the current roadway ego vehicle will decide whether the lane change is possible or not [35].

3) Model: The focus of the measurement model is to interpret observations of all the usual movement of the driving situation and the critical conditions through an accumulated belief in the state-of the system. The observations include discrete-value elements such as the number of lanes and continuous-value elements such as the distance to the front vehicle. In the event of a vehicle shifting from its own lane to the second lane on the highway, we analyze the condition evaluation of multiple vehicle collisions. If a high or low speed vehicle enters its second lane on its own lane, it can collide with the second lane's forward (rear) vehicle and the collision can cause subsequent collisions. We analyze whether multiple vehicle collisions are stimulated by the incoming vehicle or not. In this case, the number of collisions depends on the initial speed, initial density, incoming ego-vehicle speed, incoming progress, sensitivity, and relative speed. Nevertheless, our RL model is seen in terms of rewarding the achievement of the goals and rewarding the work of the partner [24], [36]. The model depicts an agent who learns to map situations to behave by constantly getting incentives from established conditions and the environment for successful behavioral approaches. As shown in Figure: 4, the RL agent responsible for environmental exploration and the RNN used in the threat assessment case defines the standard way of the component, is designed to enhance the learning of two trainable components. The learning process of the RL Agent continuously explores and interacts with every environmental state. Researchers and practitioners have often trained them via models so that they can obtain even misleading outcomes from successful exploration. The RL agent will then learn the actions associated with the recompense values and therefore create a map of these situations. This mapping is based on the compensating values of each state to identify the risk level according to the situational forecast as high, medium and low. This method can be used rather than manually labeling as an extension to control processes in which the state area is protected or not. To create such a mapping the output of the RL agent is used with the reward function specifying the degree of seriousness of risk in each state action pair. The neural network component then moves the entry to measure it more against the risk and protection level in the variance mapping so that it enters a fault-safe way if the entry is in a terrible place. Another side of RL is that this method is stronger because of the generalization to other environments of the limiting factor of additional hyper parameter tuning for an agent. The benefit of such a structure is that rewards and objective functions may be developed to unite with human intuition more closely and thus make the scheme more acceptable to human prospects. In our investigation certain facets of the condition of the system can be found and obscured. The variable of unknown conditions contains details as to whether a lane shift is feasible or desirable in the current situation, where or how long is best to go, etc.

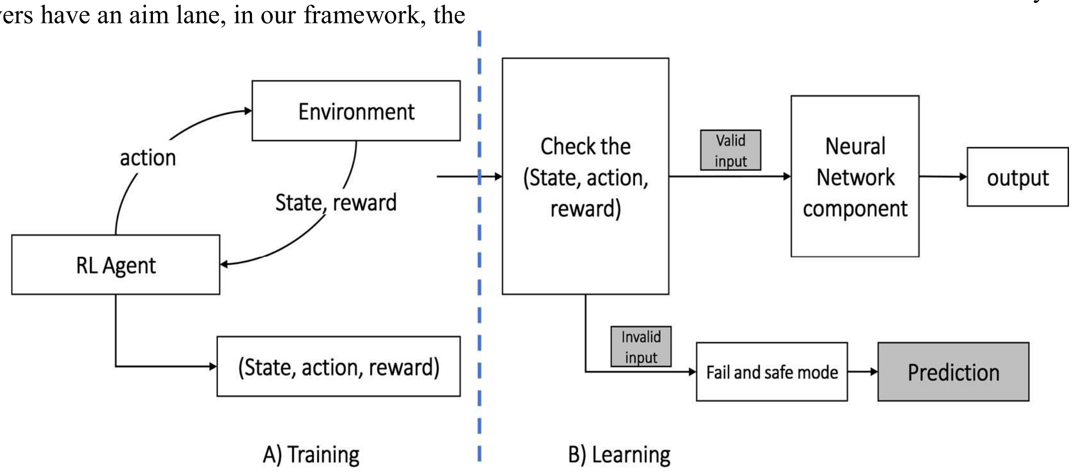

Figure 4: Reinforcement Learning based (with hand made RNN) exploration flow

C. Validity

In terms of the validation threat in the simulator (CARLA), we are not generalized to the driving environment's various driving patterns due to the map and algorithm limitations.

Thus, we have diminished such internal risk threat to evaluate different patterns from the provided map. On the other side, due to the external threat to validity in any multiple autonomous and conventional vehicle environments, we intend to present the safety violation assessment framework. However, this framework is developed only in the CARLA simulator. Our future work direction will employ the implementation of this framework in other autonomous driving simulators.

IV. Conclusions and Future Work

This work proposes a conceptual framework to investigate the causes of multiple vehicle collisions in autonomous driving systems and in-depth investigation on the aspect of lane change. Safety engineers and Automated Driving Systems (ADS) developers can deploy this framework to build multiple vehicle collision threat assessment strategies to improve the autonomous systems. Initially, we highlighted the severity of multiple vehicle collisions and showed the concept of safety measures as a solution to this problem in terms of collisions among multiple vehicles caused by a lane change. To mention some worthy indications are A) We would like to extend the framework to include others critical conditions that induce multiple vehicles collision e. g. Multiple vehicle collisions caused by the sudden slowdown of the leading vehicle, and multiple vehicle collisions because of bad weather. Furthermore, we would like to evaluate the effectiveness of this approach and suitability in identifying safety violations of driving functions from a system inventor and safety engineer perception.

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